ABSTRACT

Title of Dissertation: A TALE OF TWO CITIES: A CASE STUDY OF PHYSICAL AND SOCIAL DISORDER IN TWO BALTIMORE CITY NEIGHBORHOODS, USING GIS AND SPATIAL METHODS

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The purpose of this study is to explore how urban residents respond to their social and physical environments--what they define as problems and how they respond to them. I focus on one large, city--Baltimore, Maryland--and then compare two very different neighborhoods within it: Federal Hill, a well-off, and fashionable, area with mostly white residents, contrasted with Sandtown-Winchester, a neighborhood plagued by urban blight and crime, and where the majority of residents are black. I use a geographic information system (GIS) and spatial analyses to explore neighborhood call rates regarding physical and social incivilities, using the traditional sociological framework of "social disorder" as a theoretical lens for exploring similarities and differences in what disorders increase or decrease call rates.

I use more commonly applied stochastic methods for much of the analysis (statistical means and ordinary least squares statistics), but I also explore, in a tentative way, the potential power of spatial methods, which are not widely used or known in sociology, to reveal more about what makes these spaces similar and different and how they affect call rate patterns.

The predictive models demonstrate mixed results when predicting variation in the call rate patterns of the two neighborhoods. Income, education, and population-density effects are consistent, yet weak, positive predictors in both areas, while other indicators (home ownership, number of vacant houses, etc.) exhibit substantive positive effects in the wealthier neighborhood but none in the poorer. Neighborhood homogeneity and stability show negative impacts on rates, but depending on the neighborhood.

I focus on how local variations in action, even under similar circumstances, may depend not only on residents' aggregate capacity to commit to change, but also on how neighborhood space is internalized as a "neighborhood generalized other" as a "community," according to George Herbert Mead, either constraining or enhancing engagement. This within- and between-neighborhood variance in the strength and direction of predictor variables, and in their capacity to predict residents' calling patterns, underscores issues of validity and operationalization regarding indicators traditionally used to measure social disorganization, and how spatial methods can be valuable corrective tools.

A TALE OF TWO CITIES:
A CASE STUDY OF PHYSICAL AND SOCIAL DISORDER IN TWO BALTIMORE CITY NEIGHBORHOODS, USING GIS AND SPATIAL METHODS

by

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List of Abbreviations

311PD	311 Calls for Service for Physical Disorder
311SD	311 Calls for Service for Social Disorder
911SD	911 Calls for Service for Emergency Social Disorder
CFS	Calls for Service
ESDA	Exploratory Spatial Data Analysis
GWR	Geographically Weighted Regression
OLS	Ordinary Least Squares

INTRODUCTION

The City has long held the interest of social researchers trying to understand the connections among city inhabitants, their social and physical spaces, their occupations, and their behaviors. Early sociologists placed the city front and center in their writings. Spencer compared our organized and functionally lived lives in cities to those of sponges in the sea “where (sponge) people are…arranged about the streets and roads…(so) they can easily appropriate food from the water as it passes along (them)” (Spencer 1914, 454). Modern cities share this characteristic. We now inhabit urban spaces that we organize to “appropriate” our needs, and, like Spencer’s analogous sponges, we encounter environmental conditions that might enhance or curtail our functioning.

Environmental aspects of where we live affect nearly everything in our daily lives; our physical and mental health outcomes (Almgren 2005, Aneshensel and Sucoff 1996, Morenoff 2003), neighborhood crime and violence (Morenoff, Sampson and Raudenbush 2001), and our ability to be socially and politically active participants in those communities (Emory et al. 2008, Gibson et al. 2002, Roman and Chalfin 2008, Taylor and National Institute of Justice (U.S.) 1999). Our social behaviors, what we do in these spaces, are inextricably linked and shaped by our environments.

Robert Park and his Chicago School’s colleagues observed the city as “an externally organized unit of space produced by laws of its own” (Park et al. 1925), making it a particularly provocative space to measure for this study. They wrote:

> The city is… a state of mind, a body of customs and traditions… of the organized attitudes and sentiments …. The city is not, in other words, merely a physical mechanism and an artificial construction. It is involved in the vital processes of the people who compose it; it is a product of natures, and particularly of human nature" (Park et al. 1925)(emphasis added).

Park and colleagues echoed Weber's *The City* (1966), in which he described the urban space as a unique physical and social location of sociological interest--one that provides particular social insights because of the co-locating of, and the interplay of, the built, *physical* environment and the human, *social* action. The city is, therefore, one of the most important spaces in which we can analyze the convergence of social action and environment. However, sociological research on agency and the urban environment has historically privileged the more deterministic stance of the interplay of person and space (Park et al. 1925, Shaw and McKay 1942, Thomas and Znaniecki 1918). Structural forces beyond the inhabitants' localities and beyond their control were conceptualized as essentially causing their actions.

But social research cannot look only at social structures, nor can it simply extract individuals and their actions from their urban contexts in order to understand the impact of place on the actions of people. Augmenting more deterministic views of relations between space, place, and agency, gives voice to those agents. It contextualizes their actions. As Entwisle (2007) notes, we need to put people back *into* place, to emphasize the synergy of relations between space and social actions and to determine whether there are typical kinds of actions that citizens execute given their demographics *and* the environmental qualities of the spaces in which they live. This useful research views residents' actions as "knowledgeable activities of situated actors who draw upon rules and resources in the diversity of action contexts"

(Giddens 1984) while recognizing those actions as contextual; the actions of residents in their environments are driven by local resources and understandings of action, but are also affected by the larger social, political, and economic structural forces within which those spaces are embedded (Merton 1938).

As urban researchers, we often begin with the city, as a whole, and subdivide it into units. We carve it into politically bounded ecological and social spaces, as well as networks of places, of human relationships. For this project, I focus on neighborhoods. However, the unit "neighborhood" is fraught with measurement and definitional issues. As Greeley states, "To try to talk about neighborhoods and ignore the vitality, the color, the emotional tug, the ambivalence, the ambiguity, the depth of feeling involved in *neighborhood as image and symbol* is to waste one's time entirely" (1977, xiii, emphasis added). The *local* identification of residents, within a given neighborhood space, acts as its own unique ecological environmental variable. As human group interaction shapes how residents feel about their own community identity, it also affects how non-residents react to and understand the residents they seeing living there.

Yet, while living in a place known as Baltimore or New York, or whatever name is associated with a certain geographic space, it is reasonable to assert that not all residents inhabit such places in exactly the same way. They are all *in it* physically and socially, but not all *of it* physically and socially; no two residents live through the same experiences in these places in the same way. Indeed, this was understood and explored by early urban ecological sociologists--especially those of the Chicago School (Park, Burgess, McKenzie, and Wirth 1925; Shaw and McKay 1942; Thomas and Znaniecki 1918). Their fundamental premise still guides urban research today: that there is an ecological dynamic to how people physically and socially occupy space. It is this elemental social condition that yields a somewhat Cartesian certitude about place and self: "You are (about) where you live." This is a kind of existential fact of life. Indeed, people often choose to live in places *precisely* because they want this type of identification. As Hummon (1990) finds community identification involves a sense of belonging as well as self-conception, a characterization of one's self as connected to a particular kind of place. Thus, we encounter the identification of persons who live in certain cities *as* Bostonians, New Yorkers, Washingtonians, Southerners, Yankees, Londoners, Parisians, Romans, etc. While people may identify broadly with large places, they often also identify with smaller, more personal places within those larger ones (see, for example, Anderson 2011).

In this study, again referring back to sociologists of nearly 100 years ago, I examine neighborhoods, as well as the more precise locales within which people experience their daily lives and shape their understandings of those spaces. I also explore how social action is the product of lived-in space, and how neighborhoods affect those who live within them. I ask one major question: How do the spaces where people live and the characteristics of those locales, and those of its residents (their demographic, and social aspects, etc.) affect their identification of, and response to, local problems?

Following Mead, I conceptualize *neighborhood* as a kind of *generalized other*. Mead (Mead and Morris 1967) notes that there is a sense in which society *itself* can be "a generalized other." He points out that groups or communities in which we are embedded give individuals their sense of unity of self, and may also be called "the generalized other." Mead goes further to demonstrate that this extends to expectations of *action* in these communities as well, that it is not enough that a person internalize the attitudes of others but that…

> "(H)e must also, in the same way that he takes the attitudes of other individuals toward himself and toward one another, take their attitudes toward the various phases or aspects of the common social activity or set of social undertakings in which, as members of an organized society or social group, they are all engaged"(Mead and Morris 1967:154-55).

Individuals must internalize individual attitudes and expectations in interpersonal relations, but the same is true for *larger* groups-- their communities--and the attitudes and expectations of behavior those spaces carry as "organized communities." Aboulafia calls these "generalized social attitudes" (1991:6) and points out that, in a community, there are "certain ways of acting under situations that are essentially identical" (Ibid).

Aboulafia (1991) points out that a person finds a self that corresponds to this larger, societal *generalized other*. The same holds true at a neighborhood level; residents have a sense of what we might call a neighborhood *generalized other*. It is at this level of the *generalized other* that locally determined normative expectations of "good and bad" are grounded and contribute to cohesive responses to the specific problems neighborhoods encounter. As Blumer and Morrione (2004:124) note, the *generalized other*, as manifested as "the voice of the community," must reflect those attitudes and definitions of situations as shared by other community members. Absent this, there is no *generalized other*.

If there is a cohesive *generalized other* within a neighborhood, residents should have similar responses to social and physical disorder, a shared sense of "neighborhood." In turn, the norms regarding action to resolve these issues should be related to a *local*, community determined, appropriate response (local residents and officials, for example). What is the appropriate form and degree of social response to a particular issue or incivility? In an admittedly limited way, I address this by examining the calls made about social and physical problems, noting variations in types of problems and their associated rates of calls. I do this by contrasting two different neighborhoods, one whose residents are relatively poor and predominantly black, and one whose residents are relatively affluent and predominantly white. I looked at how municipal responses to the different kinds of reported problems (and other co-existing issues) varied and at how official responses to the same kinds of reported problems varied. Variation in call types and rates were expected to reflect not only the between-neighborhood differences in residents' capacities to react to problems, but also variances in local normative expectations about, more fundamentally, which issues residents perceived to be problems worth reporting and addressing by making those calls.

Study Organization

In the first chapter, I have introduced the dissertation. In the following literature review, I explore more deeply the conceptualizations of neighborhood, agency, and action, and important theoretical findings and research on neighborhoods in action. Having noted the most relevant studies, I next derive my hypotheses from the background theory, research goals, and methodologies employed. I then discuss the data and methods I used to test these posited relationships. This includes a lengthy

Methods section. While the bulk of my analysis is descriptive, emphasizing the ways in which my chosen neighborhoods are similar or dissimilar, in a very exploratory way I use a more complex, nuanced statistical approach that is considered unfamiliar territory to most sociologists (Entwisle 2007, Guo and Bhat 2007, Kikuchi 2010). I do this to extend my descriptive analysis and to see if such an approach, even in a limited way, is informative, perhaps suggesting causal linkages that would otherwise go undetected. In the last chapter, I summarize my key findings and theoretically interrogate them, as well as discussing briefly the utility of my methodological/statistical approach.

LITERATURE REVIEW

Theoretical Perspectives

Defining and Measuring Neighborhoods.

One of the most contentious components of studying neighborhoods is just what constitutes a neighborhood. Is it where one lives? Where one works? How long must it exist before being called a "neighborhood"? Do social interactions, either deep or fleeting, shape a neighborhood? Is a neighborhood a space with fixed boundaries? …historical boundaries? …political? …natural? In addition, each definition of neighborhood used by researchers tends to focus on particular, essential, characteristics found locally. These include the presence of specific institutions, official recognition of a named space by government, a general local agreement that the space exists as such, measures of effective organization of the residents therein as well as their networks of social relations/acquaintances, the clustering together of like-minded persons, the presence of a visually distinct area (historical architecture, green space, etc.) or of a clearly defined and bounded geo-political area (Brower 1996). Compounding the definition of the space that constitutes neighborhood is operationalizing what measures will be used to show it exists in the first place. I review some of the definitional and operationalization issues below.

The Chicago School measured spaces as progressively inclusive, spatially nested units of analysis (Figueira-McDonough 2001), with the flexibility to allow adjustment of the unit of analysis to the phenomenon of interest. At the smallest resolution level, we find interpersonal interactions with familiar persons (our neighbors or the "block level"), while at the level above, these same persons find themselves constituents in a space, usually given a name recognizable by them and outsiders and sharing the same local facilities (Ibid) and living "as a mosaic of little worlds that touch but do not interpenetrate (Robert Park, in (Brower 1996:2).

Figueira-McDonough (2001) notes that census tracts are often used as the base unit from which neighborhoods are derived because of the readiness of available data. But as administrative units, census tracts are overly rigid and fail to capture how "(e)ach separate part of the city is inevitably stained with the peculiar sentiments of its population" (Park et al. 1925) p17). Baltimore is composed of 225 such spaces. But when people are asked where they live, they do not give a census tract; they provide a *name* connected to a *space*. For this study I began determining the unit size for analysis by trying to use something that encompassed the symbolic and social meaning of neighborhood in Baltimore. With an overall population in Baltimore of about 600,000 persons, about 25,000 persons lived, on average, in each neighborhood. That is much higher than what Warren notes is the "imaginary village corresponding to a population size of about 500 families, [and]…between 2,500 and 5,000 persons" that constitute "neighborhood" as a conceptual unit (Warren & Warren, 1980, p11, in (Figueira-McDonough 2001). I was careful to choose neighborhoods that more closely aligned to the 2,500 to 5,000-population range.

Beyond population, Schwirian (1983) notes that the key elements a neighborhood has are "…people, place, (an) interaction system, shared identification, and public symbols…" and that it can be defined as "*a population residing in an identifiable section of a city whose members are organized into a general interaction network of formal and informal ties and express their common identification with the area in* *public symbols*." (Ibid, 83). Schwirian also contrasts neighborhoods with "residential areas"--spaces with few or no patterned relationships--and notes that neighborhoods and residential areas can move from one frame to the other and back again. However, his core definition of *neighborhood* remains contingent on social networks that act as the "glue" which binds people together into those *meaningful* spaces, not just a random crossing over and use of facilities and infrastructures.

While social ties are important, Sampson (2003) argues that, in the modern city, people's interaction patterns have changed; we are witnessing neighborhoods with far weaker social ties than existed in the traditional neighborhoods of the past (Putnam 2000). Today, people are able to achieve many of their instrumental goals without the strong ties and face-to-face interactions that supposedly make up neighborhoods. In fact, Sampson (2003) points out, citing Granovetter's landmark work on networks, that overly strong ties can, in fact, *impede* a community's ability to share certain kinds of information; by comparison, weak ties, that is less intense personal connections, can help to integrate groups that would have otherwise remained unconnected (Granovetter 1973). In that analysis, not only the ties, but also their quality, define neighborhoods.

Using the politically bounded, preexisting entities that are *called* neighborhoods is fraught with theoretical and definitional challenges. For example, David Harvey notes that the interactions we have in spaces occur in spatialities governed by "a more or less durable sort" constructed by and through the institutions these spaces are found within (Richardson and Jensen 2003); actions happen in defined localities so shaped, theoretically and conceptually, by a culture's institutions and by the "actions" done in those spaces. These constructions Lefebvre notes are social spaces produced through *social practices* (Lefebvre 1991). He elaborates:

> *Spatial practice* thus simultaneously defines: places--the relationship of local and global; the representation of that relationship; actions and signs; the trivialized spaces of everyday life; and in opposition to these last, spaces made special by symbolic means as desirable or undesirable, benevolent or malevolent, sanctioned or forbidden to particular groups." (p288, emphasis in original)

Neighborhoods then are contingent upon more than Schwirian's symbolic meanings and Sampson's "ties." They include the relation of those spaces to understood meanings of those spaces, as constructed through global and local practices, and through individual and institutional interventions.

Consider first the implications of using pre-defined neighborhoods, as they are known in Baltimore city, such as Pigtown, Highlandtown, Edmondson Village, Charles Village, etc. Many are historical, some are newer, some older, some are impoverished, and some are still well off. However, *none* are devoid of the symbolic impositions that Lefebvre mentions. None can avoid the meanings imposed on them by the social, institutional, and economic systems that brought them into being and continue to shape them and their *meanings* today as they are constructed, re-constructed, maintained, or deconstructed as part of social practices. Patterson Park is "up and coming" (at least until recently), while Highlandtown's meaning is shaped by the large and relatively new influx of Central American immigrants. When it was time for ex-President George W. Bush's daughter Jenna to choose a Baltimore address, she chose Federal Hill. When she moved in 2011, however, she had a hard time selling her house, not only because it had the highest price in the neighborhood, but more likely because, as she said, "The neighborhood is Federal Hill (or just south of it, depending on who you ask)." (CBS 2011) That comment, "depending on who (sic) you ask," clearly meant that not all agreed that her house was in Federal Hill; and that ambiguity was problematic.

It is important then to consider how choice, shaping, labeling, and implied meanings of *any* boundaries we pick for neighborhood units are themselves part of a systematic culture of valuing and de-valuing spaces (part of Lefebvre's social practices). They shape the meanings of those spaces and the perceptions of residents and outsiders. They mold the behaviors that people will engage in there.

Richardson and Jensen add to Schwirian's symbolic spaces the importance of acknowledging the relation of those spaces to one another. They note "spaces and places are not isolated and bounded entities, but are material and symbolic constructions that work as meaningful and practical settings for social action *because of their relation to other spaces and places"* (Richardson and Jensen 2003, 11, emphasis added). Picking "neighborhood" units of measurement acknowledges spatial practice biases while it recognizes factors like proximity to *other* entities that shape and define that space as well.

For this research, neighborhoods are considered dynamic entities, units unto themselves, existing because they produce their own qualities of space (de Certeau 1988), while recognizing those spaces are a product of spatial practices. Given these qualifications, the determination of "neighborhoods" in this study will be based not only on traditional measures, or political boundaries, but also on far more social and organic entities. This methodological approach follows Brower's (1996) assertion, that too often built form is equated with social organization and the *appearance of* community and neighborhood space. Accordingly, for the purposes of this research, *neighborhood* is a spaced defined by *action*. It is a locale of carved out activity spaces, where residents demonstrate common responses to immediate and impinging concerns and issues. It adds then to the culturally-understood, and politically-bound geographies that constitute a place "a neighborhood" by looking *within* them, to see what the actors are doing there, not just what lines on a map, or streets in the area, otherwise bound them.

To develop these neighborhoods from the "inside out" (Brower 1996), I used spatial analyses to permit emergent possibilities of neighborhoods to form more organically around measured social-spatial practices--calls for service made to 911 or 311 by local residents. I aggregated these into clusters, while still using geo-political boundaries to tag each call with a locality. Doing so unbridles the spatial constraints that historical and political definitions impose on these neighborhoods when we use census tracts alone as the neighborhood definitional frame (Coulton 2012). Defined using abstract lines on maps, administrative boundaries unrealistically push the collection and analysis of data events *into* these units--units whose contexts and contents are not at all similar. As Coulton notes, just because residents live in geographic proximity, that does not mean we can assume their perceptions of that neighborhood are the same (Brower 1996, Coulton 2012). Allowing *neighborhood* to emerge, as an object based on call patterns and spatial activity, rather than assuming delimited, pre-existing boundaries are adequate frames for these spaces, permits more naturally existing entities to emerge and provides new opportunities for analysis and exploration.

Literature on Social Indicators

Social indicator work was born in the 1930s Great Depression era, as Hoover's President's Research Committee on Social Trends attempted to manage the economic fallout and its devastating social effects (Duncan 1974). The 1960s saw an explosion of research in the field, with social indicators becoming more popular as part of a shared vision of President Johnson's "The Great Society" (Smith 1981). At that time, scientists, economists, sociologists, and politicians turned to social indicators to understand the dynamics of a society of "haves" and "have nots."

However, the modern social indicator acted as a "... direct measure of welfare… subject to the interpretation that 'if it changes in the "right" direction, while other things remain equal, things have gotten better', or people are "better off" (U.S. Dept. of Health, Education and Welfare (1969:97, quoted in (Anderson 1973). While useful in some respects, these protocols neglected to acknowledge the *motivations* behind the research for using social indicators in the first place. The fact that indicators were used to heighten awareness about *specific* issues (often political priorities) and to meet *particular* social policy objectives raised concerns about the objectivity and validity of social indicator research and findings (Ibid). Essentially, social indicator research had become "the tail wagging the dog," leaving causal models developed during the Great Society burdened with "the failure of research…to go beyond the collection of individual indicators of quality of life that lend themselves to little more than a description of what has reflected the lack of a prerequisite methodology" (Anderson 1973):286).

Through the 1970s, continued difficulties in methodology and the application of social indicator research findings were compounded by poor data and ill-fitting causal models, resulting in a decreased interest in this research area (Smith 1981). Research interest regarding neighborhoods and using social indicators declined further during the 1980s when Reaganomics, with its trickle-down social and economic wealth policies, created little motivation for investment in government programs that were, otherwise, framed as left-wing social engineering efforts and projects.

Smith (1981) pointed out how increases in social-indicator use suggest a strong political ideology and a particularly liberal bias in which government is seen as an active and accountable partner in the identification of problems that ought to be corrected in society (Ibid). This bias then shapes the selection of indicators themselves. He stated:

> Value decisions have to be made a priori about what social conditions… are to be measured and after the coverage is decided upon, one has to evaluate how the measured condition relates to the goal... (T)hese decisions must be primarily based on value judgments and cannot be automatically derived from the social indicators themselves. (Smith 1981).

Clearly, the assessment of social wellness, including measures of environmental and spatial factors affecting the social world, is not so easily disentangled from political or even neighborhood values of how people think the world should be. However, regardless of political bias, and even within the context of the methodological problems with identification and definition of social indicators, we can say there is some utility in using this kind of measure. Ensuring that social indicators are useful requires that we address their proper operationalization and note the constraints on their generalizability.

Social indicator research continues to apply measures to determine the utility of particular public policy initiatives, their actions, and impacts. However, social indicators used to make connections between economics and wellness (defined generally as a state of well-being, increased longevity, etc.) have been shown *not* to be good proxies for wellness per se (Land 1983). Most recently, McGillivray (2007) questioned the knee-jerk use of economic indicators such as GNP/GDP (gross national product/gross domestic product) as proxies for "good living," saying that, at best, such things are "only a partial measure of …well-being." Des Gasper (2007) also espoused a clear dislike for the hegemony of economic indicators and a need to acknowledge time and lived life as part of an analytic frame of social and physical well-being, saying "Even a utilitarian rat... lives *in time"*(29.) Des Gasper includes the *process* of living, of "becoming" well, as something experienced as part of our lives as lived in our neighborhoods. It is our commutes, our garden planting, our playground painting, our day-to-day "bullet-dodging", and our life passages in these spaces that matter. And that are not necessarily captured by such social indicators as "economic utility".

Still, economics audaciously dominates our conceptualizations of social indicators to the point that we forget that their purpose is not one simply of utility measurement, rather it is one of *wellness*. Worse still, socially and politically, we seem committed to pursuing their use and finding a place for them in our research no matter how poorly operationalized they are or how inaccurately they reflect the reality they try to explain. In order to avoid the "utility versus quality-of–life" debate and the reliance on unworkable solutions, both endemic in social indicators work, we need to include people's actions as part of the analysis (de Certeau 1988, Des Gasper 2007, Entwisle 2007). We must include *the actions of the people* experiencing those environments in our social indicators analyses. To do this requires that we connect people's actions to the actual indicators themselves.

In this project, calls-for-service data represent citizens *in space* generating action requests about *quality of life,* which are then adapted at the government end as measures of the utility of government function. This model of citizen-government interaction is meant to ensure a responsive government, but it also has an important, secondary, outcome: the "production of loyal citizens" (Schellong 2008). Known as Citizen Relations Management[1] (CRM), it focuses first on government performance, and then on residents' life satisfaction or neighborhood well being. However, the "loyalty" that the CRM model produces can also build citizens as neighborhood agents, effectively linking citizens to government.

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[1] Known in the field as CRM, Schellong (2007) defines CRM as "...a strategy and set of management practices, enabled by technology with a broad citizen focus, to maintain and optimize relationships and encourage new forms of citizen participation."

[2] The primary focus remains on establishing the validity of the spatial measurement protocol and on interpreting differences between neighborhood variations in calling patterns. Assuming the protocol

This same model of government-citizen is typified in Baltimore City's *Citistat,* a calls-for-service system that provides a "one-stop shopping" service hub for residents requesting government assistance with issues that affect quality of life. Each agency is also responsible for producing response reports that measure the timeliness of response to citizens' concerns, or the utility of functioning. Arguably, while utilitarian in its main purpose, this model also brings citizens closer to their government and provides citizens with efficacy-related outcomes (Bandura 1997). Yet, the measures, as collected by governments in this manner, remain only *descriptive* in nature. They tell us how many people called, where they called from, how many potholes were filled, what crimes happened where, etc. However, those measures do not tell us the answers to questions such as these: Do residents from different kinds of neighborhoods call about different things? Do factors such as race, class, education, and health affect this citizen efficacy?

The link then of citizen agency to social indicators includes the events but ignores how other social factors merge with, or influence, how they mediate or moderate, perceptions of these citizen's environments and then, how those environments support or discourage action by residents living there. The "transformative capacity of social actors" (Gecas 1989) in these spaces is left atomized and immeasurable as the actors, the events in that space, and the contexts themselves are rendered *aspatial* and decontextualized – nothing but "individuals" in a census tract, for example. To make social indicators truly meaningful, we must situate these persons, these events, and measures *in* space by acknowledging the interplay of all these components. Yet, social science methodology divorces social action from the elements and qualities of the space in which it occurs it means social indicator measures will continue to arrive at *pseudo*-spatial conclusions with that data (see (Sampson 2002) for a critique).

For example, the number of citizen calls in a census tract might be compared to the one beside it and found to have higher rates than the other, but are they *really* different? On the other hand, population-adjusted rates in different tracts are used to identify "hotspots" of city crime, but is that an accurate assessment? Such social indicator comparisons are helpful as *descriptors* but they <u>do not</u> measure the spatial relationships between actors and environments; consequently the ability to draw reliable conclusions about relationships of actors in them is impaired. Spatial measures augment traditional analyses of social indicators to include the impact and qualities of events such as their proximity, density, spillovers (one event/perception carries over into the area next to it), plumes (events 'carried' through space--most often pollution), growth and decay effects (how over time impacts may increase or decrease) and how events also degrade *across* space (Goodchild 1996).

The utility of a spatial analysis methodology married to social indicators occurs when it moves results beyond *descriptive* "maps" to analyses of events that include not only the locality but also their relationships *in* those spaces to one another. The inclusion of space as a variable, as part of the analysis is important because "…space provides the conceptual and analytical framework within which data can be *integrated, related, and structured into a whole*."(NRC 2006). The usefulness of social indicators cannot be appreciated as whole or complete until they are used within a spatialized research methodology.

__Literature on the Importance of Spatial Analyses in Social Research__

Spatial analysis involves the complex examination of "difference (that) occurs unevenly over space and through the construction of (and struggles within) specific places" (Panelli 2004). It is not simply the comparison of two data points *in* space, one to another. Spatial analysis is more than "distance from" or "proximity to" a person, group, event, neighborhood, network, etc. (Goodchild 1996); yet sociological studies of social problems data have long used aspatial techniques to draw conclusions about patently spatial issues; our research is still hobbled by our lack of recognition and employment of spatial analysis techniques (Sampson 2002).

For almost a hundred years we have been analyzing the built-environment's impact on human action and association. Known collectively as social disorganization theory, classic works on urban space, like *The City* (Park et al. 1925), The *Polish Peasant in Europe and America* (Thomas and Znaniecki 1918), and Shaw and McKay's classic 1942 piece on urban environment and delinquency have illuminated our understandings of how the well-being of individuals in urban spaces is affected by that space. Decades later, there is a renewed push by criminologists, social psychologists, demographers, geographers, and other social scientists to overcome social disorganization theory's main shortcomings by developing new theoretical and methodological techniques. Sampson et al (2002) highlight that "only recently have we witnessed a concerted attempt to theorize and empirically measure the socio-interactional and institutional dimensions that might explain how neighborhood effects are transmitted."

Misunderstandings of what constitutes spatial analysis inadvertently result in erroneous claims of *spatial* relationships (Sampson, Raudenbush and Earls 1998). For instance, it is common to see research that draws conclusions about variations in data from two locations and then attributes causation and differences to those locations, without using proper analysis tools. Measures from different census tracts and their respective correlates with other census tracts, or a regression equation that associates x number of independent variables with some particular outcome in a neighborhood, may be presented as legitimate findings. However, there may be factors located *within* the fabric of event relations that are not captured, corrected for, or re-weighted for their spatial influence. For example, how far away is one finding from another? Where does its influence start or end? What events must take place in the same location in order to produce a tertiary event? All of these questions are spatially *dependent* issues that cannot be addressed with traditional, aspatial, and techniques of analysis.

Yet, the incorporation of spatial analysis into methodological steps and assessments of data in social science research has been slow in coming. In *Putting People Into Place* (Entwisle 2007), Barbara Entwisle, a demographer, emphasizes that the critiques of Sampson et al, reported in 2002, *still remain unaddressed*--especially those recognizing the need for longitudinal measurement of neighborhood characteristics and their respective residents. Accordingly, this study attempts to move some of these issues forward by privileging spatial analysis, yet incorporating the main tenets of social disorganization into that framework. This study builds on social disorganization as a foundation, recognizing that issues of urban distress *are* problematic in the maintenance of social cohesion; this study then augments that foundation by acknowledging that the agency of those living in urban ecological niches must still be recognized. Importantly, new research looks at local/micro spatial as well as temporal variations in crime patterns (Groff, Weisburd and Yang 2010), while integrating and connecting social disorganization structure *with* these analyses. While Kikuchi's recent text *Neighborhood Structures and Crime: A Spatial Analysis* (Kikuchi 2010) breaks important ground by connecting structure, space, and time as part of neighborhood analyses, it remains more about the *techniques* of researching them without exploring *why* these intersections (space, social structure, and temporality) affect crime outcomes as they do (Hipp 2011). While this research is constrained by its examination of a snapshot in time of the studied neighborhoods, it attempts to address Hipp's critique—determining "why" these variations exist in space--before moving ahead to temporal analyses.[2]

Incorporating Spatial Analysis Into Social Research.

Entwisle (2007, 269), points out that "magnitude(s) of neighborhood effects" are also not properly addressed in most studies. These can only be assessed and properly locally contextualized with spatialized, statistic modeling. This project creates

[2] The primary focus remains on establishing the validity of the spatial measurement protocol and on interpreting differences between neighborhood variations in calling patterns. Assuming the protocol proves valid, the data set *could* be used in longitudinal analyses as it contains no less than five years of resident-reported call requests. Combined with other "snapshot" data (census measures) it could be possible to extrapolate measures and to model longitudinal changes in community call-response patterns at micro locations, as well as changes in demographic and spatial characteristics (not just call/crime rates) over time.

visualizations of these neighborhood effects as mapped layers of variations. Much like temperature maps seen in weather reports, the maps show spatial variation of effects across the city landscape, including aspects like event density in a given neighborhood, spillover effects (where an "event" appears to bleed across boundaries and into adjacent spatial areas due to its impact), synergy effects (the convergence or confluence of events in the same spaces), and decay effects (impacts that decrease across space and over time). After the removal of the artificial constraints that political or other artificial boundaries impose on data aggregation, computed local effects are liberated and displayed in an organic manner which may more accurately depict the reality of the events being measured, "on the ground," in a given space.

Literature on Neighborhoods in Action, Structure and Agency

Research on the urban environment and its inhabitants has traditionally followed a deterministic model of agency. The Chicago School's "social disorganization" theories in particular (Park et al. 1925, Shaw and McKay 1942, Thomas and Znaniecki 1918) guide this rhetoric and continue to be applied in both research and application settings (Bottoms and Wiles 1997). But those theories miss elements of the environment that play into agency, such as the existence and benefit of deep networks of social ties among residents in distressed environments. It is probable that the theory is over-predictive of crime itself, that it remains tautological in its predictive power (Granovetter 1973, Sampson 2002), and that it understates the importance of the perceptions and *experience* of an environment. Take, for example, the experience of the presence of gangs in a neighborhood and the fear they might illicit from residents (Duncan et al. 2003). Yet, social disorganization theory continues to be employed, using its ecological space measures of neighborhood stability, population turnover and resident heterogeneity to predict crime and the *poor*-being of residents in those spaces (Bottoms and Wiles 1997, Bursik and Grasmick 1993), while giving short shrift to the agency of those who live there.

Functionalist approaches to human agency consistently give primacy to structure over agency. Yet, we must come to understand how human agency is limited or enhanced, indeed provoked or motivated, by the spaces we inhabit. Furthermore, while agency is generally used to denote the actions of *individuals* in the social world, it can also be applied to larger social units, collectives that act together as one entity (Ritzer 2005). Anthony Giddens addresses these imbalances that exist with his structuration theory. He explains how the study of human agency ought not be the privileging of either "the experience of the individual actor, *nor* the existence of any form of societal totality, but *social practices across space and time*" (Giddens 1984, emphasis added). For Giddens, human agency is about the *interplay* of social structures and agency in particular spaces of action. Lived-in spaces cannot simply be reduced to "pathologizing arenas of action" (Almgren 2005, 220) without acknowledging the place of structure and social action within and *on* those places. Actions are made possible in these locales, say through the expectations of a *generalized other*, and reverberate within and throughout these environments, both building and destroying physical, political, and social spaces and possibilities.

An analysis of human agency then, especially within a neighborhood, cannot remove people from the spaces they inhabit, nor can the structures that influence them be considered as either separate or all-directing. Both structure *and* agency shape and influence one another, and individuals affect and are affected by locality.

Accordingly, measures of agency must take into account the context of the actors' environments, as well as how those agents perceive these spaces *and* the effects of their actions in them. To accommodate this interplay of the individual with neighborhood, structure and agency, and vice versa, the project then investigates residents' actions in two very structurally different neighborhoods. It incorporates environmental and demographic variables that predict and shape the actions of residents not only in response to structure, but according to differences in neighborhood social and environmental expectations. The research approach used here then attempts to supplement the sometimes overly deterministic view of social action found in social disorganization theories. This approach ensures that "voice" is given to other elements influencing action in these spaces, while re-situating the individual, as actor, in those spaces again (something Entwisle, cited above, suggests is sorely needed).

While his philosophy is often considered the realm of "one person versus the many," Giddens pointed out that we must consider the efficacy of social actions as *collective* social enterprises, not just as atomized, separate, or individual events (1984). Bandura echoed this sentiment when he described self-efficacy as "[the] belief(s) in one's capabilities to organize and execute the course of action required to produce given attainments" (Bandura 1997). He also expanded on individual efficacy, noting that, while based on individual experience, but even if learned vicariously, individual efficacy becomes amalgamated into an *entire community* of action (Bandura 1981), what Bandura refers to as *collective efficacy* (Bandura 1986). Collective efficacy at the neighborhood level represents residents who believe their group has the capacity for change and can be mobilized to alter their neighborhoods, politically, socially, and environmentally (Stryker, Owens and White 2000).

With these points in mind, agency and efficacy can also be researched as aspects of action for neighborhoods. Giddens goes on to explain how neighborhoods then can be seen as "diversity-of-action contexts," urban environments that develop as naturally occurring action spaces, rather than as spaces that are politically defined, bounded, and researched as such. Given that agency and efficacy can be locally situated, then "calls for service" made by residents trying to address problems, and change their physical and social environments, can be used to observe collective action-outcomes.

While Bandura (1997) shows individuals act as efficacious agents because *they believe <u>others</u> are acting along with them* and because *they've seen* or *heard <u>people</u>* doing "something," the vicarious learning is not only individual-to-individual, but also, more generally, related to the space they inhabit. Where people live can influence not only what they perceive as "normal", but also whether or not they believe their local space is one where they can act to alter that immediate social and environmental context.

Franzblau and Moore (2001) demonstrated how the transmission of collective efficacy potentialities is embedded within the local social, political, and physical environment, and how structure and agency intersect each of these constructions in a particular locale. For example, they find that inequality, as a form of social deprivation, affects entire groups of individuals and their efficacy expectations as well as the effective socialization of those efficacy expectations to their neighborhood peers, persons living in similar social locations and physical spaces. This emphasizes again that neighborhood residents, their expectations, and their actions are, in fact, situated in space and place, not just within abstract social structures. Locality then shapes not only an individual's capacities for action but has the potential to impact the agency of *entire neighborhoods,* as collective efficacy is learned and passed on to others, as residents socialize one another about expectations for *effective action*. Put another way, an entire genealogy of social expectations contributes to the "good neighborhood's" positive actions yet another's history might preclude efforts being seen as producing results, so not worth pursuing.

According to the Chicago School, social cohesion, found in the most organized communities, supports unified action against social norm violations. Following logically, collective efficacy is enhanced when members of the community act together, using agreed-upon informal social controls to rein in behaviors that run counter to their neighborhood's vision and its cultural norms (Gibson et al. 2002). But Sampson, Radenbush, and Earls (1997) and Morenoff, Sampson, and Radenbush (2001) challenged whether or not social organization itself is enough to answer the question "Can residents work together to make change happen in their lived-in spaces?" To address this, they refined the concept of neighborhood collective efficacy to include individual perceptions of how supportive a neighborhood might be of an *individuals' execution* of informal social controls that could shape that space. While environments can be highly integrated and homogenous (racially, economically, educationally, etc.) it remains to be seen if those same neighborhoods exhibit *social cohesion* and the trustworthiness that enhances individuals to act, to look out for one another.

If we contrast the generally accepted perception of collective efficacy (the ability of individuals/groups to act) with the defining property of the social disorganization theory frame (that is "the inability of local communities to realize the common values of their residents or solve commonly experienced problems,"(2003, 327), a theoretical contradiction emerges. Given that there are distressed communities with *high* levels of social organization (they have community organizations, set their own normative expectations, and instill informal social control structures there etc.), and that there are also distressed and highly socially *disorganized* neighborhoods, it remains to inquire "Is crime and environmental decay the best, general explanatory factor that affects residents' perceptions of self-efficacy?" While evidence persists to counter social disorganization theory's shortcomings, and criticisms of the theory have been many, the role of different neighborhood *contexts* and how they impact differences in resident actions, remains, largely, uninvestigated(Browning, Feinberg and Dietz 2004). The role of environmental space on efficacy for these differently "disorganized" spaces then remains untested.

How then might we measure social action while incorporating neighborhood context as an important factor? Sampson et al. (1999) noted that collective efficacy is a "task specific construct" focused on the mutual engagement of adults and the execution of informal social control actions directed to desired outcomes. I propose that, with the action of picking up a telephone and calling in (or going "online" via the internet) and reporting a problem for remediation, residents are effectively expressing a willingness to exert informal social control over fellow residents and local, physical incivilities. They are attempting to address issues and problems that run counter to their normative, expectations for their neighborhoods, how they think they ought to be as particular, social and physical environments. The issues that residents call about indicate what is or is not considered normal, tolerable, or intolerable in these specific spaces. The "calls for service" database then, with data on the offending incident or problem, coupled to the caller's geo-location, provides special insight into acting individuals: spatially-situated, resident-agents, people trying to act on their neighborhood conditions as well other residents' behaviors. These calls then illustrate a specific kind of collective efficacy then where the local rate of calls reflects that neighborhood's expectations as well as learned belief, that the residents can, and indeed should, attempt to influence their social and physical environment.

This proxy for social action, "calls for service," represents residents and citizens of neighborhoods whose actions are shaped by the particular experiences of living in a spatially situated cultural world, one that is affected by additional structural influences. As individuals make "calls for service," they represent a measure of collective efficacy, of that neighborhood in action. Actors then, in neighborhoods, are not isolates. They see their neighbors exercise social control over others' *specific* behaviors and over *particular* issues with *particularly* valued, or abhorred, qualities. Residents learn too that city officials and agencies will or will not act on their requests in those spaces (Gecas 1989), and whether their own energies are being expended without reciprocity or result. These experiences reinforce whether residents believe themselves to be efficacious as actors in that neighborhood proper.

Grappling with Spatial Definitions--How can we graft "Neighborhoods" onto "Action Spaces"

Gerald Suttles (1972), in his important text *The Social Construction of Communities,* notes that although there exist synonyms for spatial areas we call "neighborhoods," such as blocks, hoods, districts, areas, and communities, our use of different words suggests that we are "grappling for more differentiated representations" of those spaces (Ibid, p55). Using a Geographical Information System (GIS) permits the analysis of spatial patterns of actions and allows the emergence of new units of spatial analysis in place of the sometimes ambiguous and conflicting definitions, conceptualizations and operationalizations of "neighborhoods" as social units of analyses. I am calling these locations "action spaces" rather than "neighborhoods of action" to reflect their fluid boundaries (avoiding the artifice of census boundaries) and, most importantly, trying to bring out the actions of those living within otherwise administratively-bound locales.

The Chicago School of Sociology identified neighborhoods as "organic" outcomes of necessary social structures and ecological sorting practices (Bursik and Grasmick 1993, Park et al. 1925). But this understanding of "neighborhood," from a functionalist perspective, largely disregards the *interactions* of symbolic understandings amongst those that live in these spaces as important to the social and spatial segregation occurring in them (Bursik and Grasmick 1993). Anderson emphasizes that neighborhoods are "not simply a consequence of social inequality but…a product of both social and spatial differentiation" and that we have to include spatial factors (proximity, density, distance, co-existence, etc.) when considering decline and decay of neighborhood spaces (Andersen 2003).

It is with these thoughts in mind that I reject the suitability of what Suttles identified as institutionally imposed and defined neighborhoods, or "communities of limited liability" (Suttles 1972, p59) as useful spatial units of analysis for this study. A community of limited liability, he said, is one in which external "adversaries or advocates" want to see the continuation of that space as some kind of named, administrative unit.

While this kind of space is symbolic and structural, it does not allow for the permeability of events and actions that is the reality of these social spaces. For example, while I was writing this dissertation, someone was shot while leaving a take-out restaurant located in the neighborhood that immediately abuts my own, as defined by administrative boundaries. As this person fled, the bullets continued to fly, until he fell and died on the corner opposite the restaurant. While he was shot in the other neighborhood, he was, for administrative purposes, murdered in *my* neighborhood (Waverly) and *not* in the tonier Oakenshawe neighborhood that abuts mine. That this victim of crime died *where* he died may cause our "community of limited liability" to respond to the event in a very focused and limited manner with a very few engaged and interested community individuals, as Suttles would say.

Murders, as in the above case, clearly can have a negative impact on perceptions of a neighborhood and can result in the depression of a neighborhood's home values (Pope and Pope 2012, Schwartz, Susin and Voicu 2003). A local community neighborhood board, with only 7-10 members, then might elect to fight that effect and develop an action plan to address problems contributing to this and other crime. And again, neighborhood impressions, events, and actions, are tied to space.

Even the word *neighborhood* conjures its own set of problems symbolically. Thus we are left with two extremes when operationalizing the spatial extent of the unit called “neighborhood” (Bursik and Grasmick 1993). Bursik and Grasmick stated that at one end of the dimensional scale are surveys that allow respondents to define the state and extent of their lived-in spaces themselves; at the other end are neighborhoods defined as strict, administratively drawn and bound units. Units defined in the latter manner directly affect data collection and analysis, and especially the aggregation of local level data. In addition, when viewing action at one extreme we find the symbolic, the resident as “agent,” while on the other hand, through the lens of institutional abstraction and bureaucracy maybe, the resident is transformed into “citizen” and stripped of individualism. Residents are subsumed in the larger unit of neighborhood, and agency becomes the output of the *neighborhood* as actor itself. One goal of this research project is to bring these two polar dimensions closer together, if possible. It attempts to move beyond the arbitrary nature of administratively constructed boundaries--ones that create “neighborhoods on paper”--by highlighting the actor/resident as someone changing and influencing different spaces in different ways. Neighborhoods become “action spaces” where residents act, not only spaces that constrain the resident structurally.

The Importance of Augmenting Traditional Research Methods with Spatial Ones

An alternative to spatial analyses is to use census data, aggregated at the block or tract level. But I counter that this methodology, and specifically its spatial resolution, is too coarse (Institute for Social Research) for the purposes of this research. These levels of resolution have been used by others in social science research, specifically by Crowder, South et al. (2006) and Quillian (2002). I address these two research pieces specifically to clarify why I am not using this practice--not as a critique of previous work per se, but to illustrate how spatial analysis methods can create entirely new, and perhaps more nuanced data, data more sensitive to the locale from which it is drawn. Crowder and Quillian's research pieces study migration patterns and use the "PSID census geocode" (Quillian 2002 , p205). However, while the PSID itself offers contextual information, and while the authors have "geocoded" their data, they do *not* follow with true spatial analyses of that data. When their models of likelihood of movement among neighborhoods explain migration from one census tract to another, the authors are using descriptive data to make their case. There are *no* spatial measures (distance, proximity, etc.) used in either research. Furthermore, there are quite contrary and direct critiques against South and Crowder's use of census tracts in their research as a methodology (South & Crowder, 1999, in Gieryn 2000).

Gieryn writes of South and Crowder's work, saying: "If a census tract is simply a bundle of analytic variables used to distinguish one neighborhood from another in terms of its economic or demographic features, then it is not a *place*" (Gieryn 2000, emphasis added). That is not to say that these other persons' research is not valuable, but rather that it lies far outside the theoretical frame of spatial analysis, whose focus is on the intersection of variables *and* place. Gieryn is not alone in criticizing the lack of attention to "place" in social research more generally. McLafferty, Williamson et al. (2000) note the dearth of attention to using place as a unit of analysis in spatial research on crime.

> "We are concerned with theories describing the influences of places on crime. Crime is concentrated in relatively few places, even in neighborhoods in which crime is common… A place is a very small area reserved for a narrow range of functions…and separated from the surrounding area. By small we mean a place is smaller than a neighborhood or a community." (McLafferty, Williamson and McGuire 2000)

However, census tracts, as aggregate units, are overly coarse (too macro), and can unnaturally force aggregation where it is not always appropriate. Action spaces, located in small spaces that can span artificial boundaries, could make for more appropriate units of spatial analysis. Action spaces capture more than descriptive elements of those places, which aggregate measures largely do, additionally including actions occurring in those types of spaces, something macro analyses lose. GIS research is effective in bridging this gap. Through increased access to information, it provides residents in neighborhoods with data and encourages citizen participation (Ghose and Huxhold 2005). By elevating the importance of place, a GIS allows *variations in geographic scale* that permit cross comparison to places similar or different, which a system using neighborhoods operationalized as units cannot do.

This research seeks to bring this same kind of focus to the neighborhood sites of interest, viewing them as complex associations and intersections of demographics and local physical characteristics that, together, render them as specific kinds of "action spaces." It attempts to see the spaces and the persons inhabiting them as more than their descriptive elements (race, class, education, poverty, decayed, crime-ridden, etc.). These spaces represent objects and research units larger than "place," as defined above by McLafferty et al.; but they still cannot be defined as corollaries to "neighborhoods" because they sometimes lack the components commonly ascribed to neighborhoods, such as shared meanings, facilities used by all, distances, population, and the locale's spatial extents. Given the definitional complexities and pitfalls of the term "neighborhood," and to permit a more organic object of "neighborhood" to emerge, I let the neighborhood action spaces themselves emerge through the final GIS data exploration steps. Unlike Crowder, South, Quillian and others who used political boundaries, this research allowed significant clusterings of calling, as spatial patterns, and similar action types to emerge and to allow the spaces, around these clusters to coalesce as their own objects, to see how they might be defined and understood on their own merits rather than circumscribing these calls with artificial containers and boundaries.

Importance and Implications of Using a Social Spatial Analysis

The National Research Council notes that "spatial thinking is pervasive: it is vital across a wide range of domains of practical and scientific knowledge; yet it is under recognized, undervalued (and), underappreciated…"(NRC 2006). While there is much talk of the importance of incorporating space and place into social research, it remains slow for the field of sociology (and other social sciences) to embrace its importance, theoretically and methodologically. The incorporation of truly spatial analyses of the social world and human interaction has become more the domain of *geographers* doing sociology, wandering into the interstitial intellectual spaces of social theory, rather than of sociologists doing the reverse (Gregory 1995).

Gregory (1995) is also critical of social science's ambivalence toward space and spatiality and suggests following the early recommendations of David Harvey (1973) that we adopt a "geographical imagination" --a purposeful parallel to, and borrowing of C. Wright Mills' "sociological imagination." He argues for an intellectual project that bridges the divide between the isolated, white, Eurocentrist conceptualizations of spaces and spatialities, of places and non-places, while pointedly noting that such a project is far from complete--nearly two decades after Harvey first made his recommendations. Aspects of race, class, gender, disability, and sexualities still remain distant and small voices in any analysis of space and spatiality in the discipline of sociology; yet we are well aware of their importance in almost every other theoretical and methodological approach in the discipline.

In this project, I fill in a small portion of that "geographical imagination" by not only using spatial analyses but by restoring "place" and the people in it into those analyses, while granting persons a deserved voice representing their agency in that space. The challenges to social disorganization that this project raises highlight inconsistencies in the agency-structure and determinism assumptions social disorganization theory uses as its ballast. When spatiality is introduced as a missing consideration, it answers some of these challenges while deconstructing the most monolithic constructions of urban environments and abstracted social relations it uses to support its assumptions. In doing so spatial analysis contributes to a more nuanced and dynamic view of urban space as well as the actors occupying it, and how these two components intersect.

This approach recognizes not just social action but also social capital. Weber's "social action" theory has long been a staple of sociology. Social capital, however, is a much more recent concept. Putnam (2000) expresses social capital as social cohesion and trust created through networks of association built up through collective action as the striving towards mutually beneficial goals. Social capital can be considered part of the equation of collective efficacy. But social capital's manifestation may be moderated by less apparent mechanisms, such as differences in the experience of spatial environments: Did you grow up in a neighborhood with liquor stores on every corner, as in east Baltimore, or did your neighborhood have a local wine bar instead and a Whole Foods market? It follows then that different environments shape styles of actions that, in turn, build different kinds of social capital. Variations in urban environments, such as concentrated poverty, education, and social disadvantage have all been found to contribute to variations in the accrued local social capital (Sampson, Morenoff and Earls 1999). Putnam's definition then may be inaccurate or, at least, insufficient in the modern urban context. This research works to elucidate some of the vagaries associated with differences in neighborhood social capital that Sampson hints at, by determining how actions differ depending on variations in the *qualities* of spaces of those living there.

Earlier I highlighted the importance of improving the clarity of definitional frameworks used in social indicators research, as well as a need to enhance the practical utility of their outputs. This research advances that agenda by testing demographic measures commonly identified and used as inputs in traditional statistical modeling to measures social disorganization. It also contextualizes them and determines if, indeed, connections can be found among such variables in the spatial contexts and extents of neighborhoods--relationships that have, largely, not been investigated to date (see Entwisle 2007: for example, Meersman 2005: for example). Meersman critiques the absence of spatial methods in sociology research and it represents one of a few sociological studies to consider and incorporate space into its research questions. However, it falls short of the mark for while his study uses a GIS to complete the analysis of data relations, his use of “buffers”, as a methodology, does not itself, constitute a *spatial* analysis of the relationships between his factors of interest, in that case neighborhood problems and health outcomes.

The same might be said of much of Robert Sampson’s seminal works on urban space and crime, where he uses less than perfect “spatial” methods that only serve to illustrate further that misconceptions of what actually constitutes spatial analyses still remain (Morenoff, Sampson and Raudenbush 2001, Sampson, Raudenbush and Earls 1997, Sampson, Raudenbush and Earls 1998, Sampson, Morenoff and Earls 1999, Sampson 2002, Sampson 2003).

For example, some of Sampson’s work (2003) suffers from methodological temporality issues. As he and his colleagues looked at crime in neighborhoods, they collected neighborhood disorganization measures during one time of day only, *midday*. Obviously, this would not be the only period of day when crime and disorganization happen. Arguably, it is the time of day when one would be *least* likely to find disorderly actions. From a spatial point of view, the researchers also chose streets as randomly as they could, while *purposefully* selecting areas they considered would be the most socially disorganized spaces. They then videotaped them, and analyzed the recorded street content for “social disorganization” objects--prostitutes, drunks, etc. While innovative, the reliance on researchers identifying what constitutes social disorganization measures remains an operationalization problem. The current research project overcomes such a methodological issue by counting events happening 24 hours a day, 365 days a year, over a three-year period, and across the entire spatial plane of a city. As such, it gives voice to differing assessments of the same events, while directing the focus back to the actions and responses to events rather than to the events themselves as being problematic because a researcher has defined them as such beforehand.

Admittedly, choosing to let the data speak on its own, as part of the methodology, could prove problematic in terms of generalizing findings to other urban spaces since it becomes open to interpretation. However, that aspect is addressed by operationalizing differences in neighborhood perceptions of incivilities as *typologies*, by comparing neighborhood perceptions of the same offensive behaviors to see how they differ in reaction and strength of action, rather than using absolute measures of "yes" or "no" as to whether "social disorganization" or "social efficacy" is present. This methodology permits the emergence of a *continuum* of social organization to disorganization while it models reactions to the problems faced in various socially and physically different landscapes.

Research Hypotheses

In light of the literature reviewed and my general sense of everyday life in some of Baltimore City's neighborhoods--especially the ones I am studying which maximize variance in race and class--I set forth the following hypotheses (with a brief discussion of each immediately following it):

> *H1 – As neighborhood wealth increases (income, education, home ownership, etc.) calls to remediate social and physical disorder issues will increase.*

This hypothesis tests, most generally, how neighborhood differences in wealth might relate to call rate patterns concerning physical and social environmental problems experienced by the two different target neighborhood populations--the more affluent Federal Hill, and the less prosperous Sandtown-Winchester neighborhood. Comparing Federal Hill to the less wealthy Sandtown-Winchester neighborhood, I expect call rates about social and physical disorder will increase as wealth increases. Here, wealth is measured as families living in poverty, homeownership versus renting, educational levels attained, and income. Wealth differences between the spaces will be used to explore how different neighborhoods--one with more resources versus another with less--might be responding differently in the exercise of informal social controls, that is, the making of calls about incivilities. Call rates serve as a general proxy for residents in action as they work to effect change to an array of offensive environments and behaviors in their respective neighborhoods, while I determine if differences in wealth translate into differences in residents' informal social control. However, why do some residents choose to focus their attention on some distasteful objects and behaviors while ignoring others needs to be investigated also. Therefore, I next explore how variation in social disorganization in neighborhoods might be affecting which situations or behaviors are identified as unacceptable.

> *H2 - As neighborhood wealth increases, the rate of calls made about physical disorder problems will decrease while rates of calls attempting to redress social disorder offenses will increase.*

The second hypothesis continues to explore the effects of wealth difference in neighborhoods but more specifically addresses how wealth shapes *which objects or behaviors* are identified as offensive to residents.

Greenberg (1999) notes that residents provided with new residential amenities, like parks, trash pickup, and schools, still did not consider their neighborhood as having improved *until crime and physical decay issues had been addressed and corrected,* and that this belief held true across all neighborhoods, not just socially disorganized ones (Ibid). Accordingly, this hypothesis tests Greenberg's findings here. As wealth increases in a neighborhood, measured as decreases in vacant houses and in families living in poverty and as increases in median income, education, and homeownership, the objects getting the most attention for remediation (rates of calls) will shift from the policing of larger, physical disorder issues and move on to more subtle physical and social disorder nuisances as the primary focus of remediation by residents. This shift will be evidenced as increases in call rates for those offenses. Changes in wealth are expected to change what objects get targeted for correction, measured as a *qualitative* shift in the types of calls being made, with more calls in wealthier spaces about issues that Greenberg (1999) identifies as "amenities" issues: things like concerns about parks, trees, or schools, rather than those about serious and immediate threats to survival, such as burned out buildings, drug dealing, etc.

This hypothesis assumes that wealthier neighborhoods are better able to marshal resources, including their own local social capital. Increased resource mobilization should bring an ability to shape and influence community norms changes; the thresholds of what will be considered acceptable surroundings (physical disorder) and behaviors (social disorder) should shift from the most glaring, physical disorder problems such as repairing a street or fixing a burned out light, to more subtle social policing and issues about "quality of life," for instance loud noises at night, minor traffic infractions, etc. For neighbors to identify things as physical or social disorder problems in the first place, they must have the capacity to do so. I predict that neighborhoods with less wealth will have lower call rates for smaller quality-of-life issues as they continue to be overwhelmed by larger crises and issues, things that force them to attend to such physical disorder and acute crime problems first.

H2 also tests whether variations in neighborhood wealth impact their generalized, normative *other,* the unified expectation that shapes residents and their understanding of themselves as residents of a community (Singer 1993). Singer says norms are developed by mutually interacting persons, who, when acting in a coordinated manner, "jointly arrive at a framework of common understandings, assumptions, directives and expectations…to govern their own behavior, to know this behavior will be interpreted and to interpret that of *others*" (Ibid, p130, emphasis added). It stands to reason then that neighborhood differences in wealth might affect the ranking of particular physical and social incivilities as more or less in need of attention and correction, while others may remain ignored, or even accepted as normative in some spaces. Neighborhoods with increased wealth (economic and social resources) should transform problem areas into spaces with increased policing and with even more homogenous or constraining policing of norm violations, as more objects and behaviors are brought under the umbrella of informal and formal social control mechanisms.

The next two hypotheses test the effects of neighborhood disorder on the rates of calls that residents make about physical and social incivilities. They read:

> *H3A – As neighborhood measures of disorganization increase, the rates of calls for service to remediate physical disorder will decrease.*

And,

> *H3B – As neighborhood measures of disorganization increase, rates of calls for service to remediate social disorder will decrease.*

Hypotheses H3A and H3B address whether wealth alone can explain the ability of residents to act. What role does the physical and social environment play in more socially disorganized locales than in organized ones? How might that be shaping local residents' and their neighborhoods' responses to incivilities experienced there? Are there differences in response by quantity or kind of issues identified? To investigate the effect of disorganization on neighborhoods' responses, I split that disorganization into two aspects: predicting physical and social disorder calls.

How might changes in physical disorder affect calling patterns? Kelling and Wilson's classic 'Broken Windows' article (Kelling and Wilson 1982) discusses the link between physical decay and crime, how criminals see neighborhood spaces where social controls have declined to the point where those spaces become hospitable to crime. In that study, the presence of police elevated the degree of public order in disorganized spaces, making residents feel safer, even if crime was not decreased. What effect does physical decay have on engagement by residents themselves in these spaces? Looking at the role of fear in community engagement, Taylor and Gottfredson (1986) reviewed research showing linkages between physical disorder and crime and fear. But they were also quick to point out that many of those connections were based on "loose, open-ended models rather than articulated theories" (Ibid, p403). Still other research shows inconsistent associations between resident participation and neighborhood prevalence of physical disorder (Swaroop and Morenoff 2006) sometimes demonstrating that even communities with high social capital can exhibit lower community engagement than those with extensive physical decay (Hunter 2011).

Twenty years after Taylor and Gottfredson's review, Swaroop and Morenoff raised the same issues (Swaroop and Morenoff 2006) . They pointed out that neighborhood context continued to be excluded when theorizing about resident participation and engagement in neighborhood activities. They stated that most studies continued to focus on ecological, rather than local or neighborhood level analyses, while physical incivilities continued to be used as proxies for social need to the exclusion of social incivilities (individuals engaged in drug dealing, drunken behavior, juvenile disturbances, etc.) as part of the analyses of the experienced environments of neighborhood residents. Accordingly, this project splits attempts to address disorder into models with predictive coefficients measuring remediation of physical *and* social disorder issues, and uses neighborhood context measures for both kinds of disorder to see how they differ in the wealthier space of Federal Hill and the poorer neighborhood of Sandtown-Winchester.

In the predictive call-rate models tested (predicting changes in calls trying to remediate issues about physical disorder, social disorder, and emergency social disorder), physical disorder is measured as neighborhood physical decay (abandoned and vacant buildings, streets in need of repair, abandoned cars, trash and litter, etc.) as well as factors that increase environmental distress within those spaces (graffiti, rats, dangerous or dead animals, etc.). Hunter notes that neighborhood civility extends beyond social actions. Friendly greetings are important but so is physical civility. Residents expect to see others behaving in ways that are supportive of community norms while enhancing their community. This includes signs of physical civility like tidy lawns and yards, and clean sidewalks. Signs of physical incivility on the other hand include things like abandoned cars, overgrown yards and lots, and littered alleys and walks (in Taylor and Gottfredson 1986). The incivilities that Hunter discusses are included individually as input variables in each of the call rate change prediction models (for example, vacant houses) and within the "311 Calls for Physical Disorder" variable (see Table 1, p 76) to test how changes in physical decay and disorder affect local resident call rates. While hypothesis *H3A* illuminates the connections between physical disorder and residents' call rates, the following hypothesis, *H3B*, explores the effect of social disorder on those rates.

A main premise of social disorganization theory is that disorganized communities are *socially disordered* communities (Bursik and Grasmick 1993), where disorder is defined as "a violation of norms concerning public behavior" (in Bursik and Grasmick 1993, 46). Disordered communities exist as spaces in which rule breakers find safe haven from punishment, where informal social control is lacking, and where people are able to multiply their violating behaviors without sanction or repercussions (Shaw and McKay 1942).

In keeping with previous research (see (Sampson 2008, Shaw and McKay 1942, Swaroop and Morenoff 2006), I have identified social disorganization and disorder variables as high rates of the following: neighborhood racial and ethnic heterogeneity, resident turnover, ratios of renters versus owners, unemployment, crime, increased population density (representing increased competition for scarce resources), families living in poverty, residents having lived in their homes for less than five years (exhibiting neighborhood instability), and lower, overall, levels of educational attainment by residents.

As noted above (Swaroop and Morenoff 2006, Taylor and Gottfredson 1986), the findings are inconsistent as to whether or not physical and social disorder affects community engagement positively or negatively. By purposefully comparing two oppositional neighborhoods, those with different demographics and privileges, I am trying to counter a criticism Swaroop and Morenoff leveled at earlier researchers, that research on social disorganization is focused almost exclusively on the poor, African American neighborhoods, rather than including a wider range of neighborhood contexts. I anticipate that the findings of this study will be more robust and generalizable, while reinforcing earlier research that shows that neighborhoods with increased social cohesion demonstrate higher levels of caller activity as a form of civic engagement and local responsibility, than a poorer, more disenfranchised, neighborhood.

While the above hypothesis tests how local wealth and capital, and differences in physical and social disorganization affect which objects or behaviors are deemed acceptable or not in neighborhoods, it does not adequately test whether or not these social expectations are *uniform across space*. Norm breaking, as a lack of deference to social authority, happens *in space*--and because it is happening in local *neighborhood* spaces, it can erode community cohesion. This erosion further feeds social disorganization (Shaw and McKay 1942).

The following hypothesis, *H4A*, examines whether higher social disorganization affects the patterns of reported events by resident-callers, generating more disparate and clustered (versus uniform) calling actions and patterns by those residents. How can we measure consistent response to problems then? Hypothesis *H4A* explores this. It reads:

> *H4A – As neighborhood physical and social disorganization decreases, clustering of calls, indicated as mapped significance values in neighborhoods, will decrease.*

Clustering is measured using spatial autocorrelation analyses which generate measures of significance, indicating how much of locally measured value is determined to be the result of *nearby* call rates, rather than of chance alone (Arlinghaus and Griffith 1996). A spatially uniform spread of responses, across a neighborhood and for a given problem, should indicate community consistency in responding to issues. From a stronger understanding of what that community's *generalized other* means to all--what will or will not be tolerated in that space by its residents--residents should call more consistently across their neighborhood, demonstrated as spatially uniform rates across space. Clustering of high or low rates, on the other hand, would indicate hyper-local, or individualized, responses to problems--citizens working things out "on their own" – rather than following local normative doctrines.

This hypothesis tests for a spatial consistency of call rates across neighborhood spaces, and does so using exploratory spatial data analysis (ESDA) techniques to reveal clustering of calls. It compares these patterns between the highly organized and highly disorganized neighborhoods to test the impact of disorganization on call clustering. It is hypothesized that high clustering of calls is a proxy for inconsistent resident social control in response to incivilities, while spatially equally distributed call rates demonstrate a unified social response across that space. This prompts me to look for patterns: Are calls appearing as pronounced concentrations only in some parts of a neighborhood? Are clusters the same for all incivility events? Alternatively, do calls display a smooth and equal distribution across a neighborhood? A highly organized community should demonstrate uniform social expectations and informal social control actions, in the form of consistent call patterns and rates across the neighborhood space. There should be no clusters of high and low rates within the highly organized neighborhood; the more disorganized neighborhood should display more fractured patterns of calling, more pronounced clustering, and variations in densities.

As noted above, the collective voice of a neighborhood can be expressed as a form of Mead's *generalized other*, replete with expectations of what is normal and how neighbors ought to behave when living in, visiting, or briefly transiting that space. Residents and visitors experience this as a reflection of local, cohesive expectations of acceptable neighborhood behavior and appropriate formal and informal social controls. These variations in what is considered acceptable or normal are directed at particular physical objects (an abandoned building or trash in the street) and social behaviors (drunkenness or abuse of an animal) found *in that space;* those that violate expectations are sanctioned while those that enhance the *generalized other* are encouraged. Determinations of what will be acceptable and unacceptable are guided by a sense of what it means to live in, or be part of, that *local* neighborhood rather than more structurally abstract, and supposedly globally accepted and pervasive, expectations of neighborhood behavior (Ibid). At the same time, community consensus (whether for what behaviors or physical markers are considered acceptable or unacceptable) must appear too as cohesive *across these spaces* if consensus is to be an *effective* component in the orchestration of informal social control. And effective application of controls, in turn, contributes to increased social organization and a lived experience of internal, neighborhood, normative consistency for the residents and persons inhabiting that space.

The Broken Windows theory supports this variation and clustering of events when it suggests that social and criminal disorder accumulates at the same locations within neighborhoods, creating pockets of crime (St. Jean 2007) as those spaces become more inviting venues for crime and incivilities. Social control, however strong or weak, supports the sedimentation of bad events and good ones. Accordingly, any analysis of response to neighborhood ills should not be randomly distributed throughout a neighborhood when high social organization is present. Highly disorganized spaces will likely devote energies to concentrated "hot spots" while socially and physically cohesive spaces should foster *consistent* responses to like offenses as that neighborhood shares a vision of what it will and will not tolerate, and maintains the social capital to marshal a unified response.

This hypothesis tests for internally consistent and spatially uniform responses to incivilities. Spatial analysis can measure the degree of "internal consistency" of a neighborhood's identification of which *kinds* of violations are problematic, as well as the *degree* to which response is consistent. A neighborhood with a strong *generalized other* should respond to problems in a cohesive manner, regardless of *where,* within its understood bounds, those ills might happen. A cohesive neighborhood (low physical and social disorganization) should demonstrate fewer "hot spots" (clustering) of high or low call rates about specific violations. While this hypothesis is effective at testing for patterns of calls about *events,* it cannot reveal how the predictive power of variables is affected-- within and between neighborhoods--by social and physical disorganization. This next, final, hypothesis explores this problem.

Macro-structural models of environment-action relationships often rely on local data aggregated to large unit levels (such as census tracts). Global data used to explain micro-located actions (such as resident phone calls) obscures those individual actions and local differences – even difference *within* these smaller spaces. It also contributes to the problem of the ecological fallacy by assuming the impact of a predictor variable is uniform across space. As an alternative methodology, this hypothesis is anchored in a different spatial-analysis method, specifically Geographic Weighted Regression (GWR). It instead explores local variations in the prediction power of independent variables while illustrating differences *between* neighborhoods in levels of social and physical organization. It reads:

> *H4B – As social disorganization increases, the explanatory power of the independent variables will show spatial variation not only between neighborhoods, but also within them.*

In hypothesis *H4A,* spatial differences in resident responses to events, within a neighborhood, are predicted to reveal more about a neighborhood's internal, normative cohesion. This final hypothesis goes a step further, however, to test for the consistency of a variable's *power* to predict variance in calls given differences in the social disorganization of the two neighborhood sites. To test this hypothesis, I used Geographically Weighted Regression (GWR) (Fotheringham, Brunsdon and Chalrton 1998) to create explanatory variables, and mapped their resulting parameter estimates, one value roughly every 250', across the two neighborhood spaces. The mapped values permit visual comparisons and explorations of parameter strength variations across space, between models, and between neighborhoods. The more organic nature of the GWR parameter estimate generation method should provide a more nuanced representation of coefficient variance *within* a neighborhood space, while depicting whether disorganized spaces display more heterogeneous spatial distribution of those values, versus the predicted more homogenous power in the organized neighborhood.

Mapped coefficients indicating the power of variables to predict variations in call rates for a given model are predicted to appear as more uniform surfaces of values, spread more uniformly across the more organized neighborhood space of Federal Hill, while wider variations in values are expected within the more disorganized space of the Sandtown-Winchester neighborhood. Additionally, if the traditional ecological model of social disorder is supported, then local measures of social and physical order/disorder (such as rates of ethnic diversity, home ownership, neighborhood stability, physical decay, and crime) should be displayed as *stronger* predictive coefficients in the more disordered neighborhood spaces than the more organized ones. Also, where mapped coefficients display similar powers and spatial distributions in *both* neighborhoods, we can hypothesize that those variables are suspect: they are producing no observable differences in valuable predicting how social and physical disorder affects calling yet we *know* those spaces to be highly different. While such lack of variance could indicate poor specification of the model and the variables used to operationalize social disorganization more generally are it importantly illustrates that that model's variable, predicting call-rates, has little to no normative effect on calling behaviors.

To test if some variables may be more or less influenced by local events and cultural expectations/social norms I compared neighborhood outputs for the same variables between the methodologies: non-spatial (OLS) and spatial (GWR) model outputs. While the results would be descriptive only, I predict where OLS and GWR results converge (that is, where their spread in values is reduced) we can suggest that those variables are the least affected by space and the locally-specific experiences and normative expectations. Finally, to determine if the model is, in fact, mis-specified I review coefficients across two or more of the call *models (*versus between neighborhoods). Assuming "calling" is an equally easy to execute behavior then all models of call types should demonstrate similar coefficient strengths, one to the next. However, where variables are inconsistent in power or direction between models they are not contributing equally to our understanding of why variation in calls (due to social disorganization variation) is occurring. The supposed to be similar outputs are being mediated or moderated then by *other* unmeasured influences. These results could aid future research and help refine the conceptual framework and operationalization of the social disorganization frame (Krohn, Lizotte and Hall 2009).

METHODS

Study Site Selection

Nearby, Yet Worlds Apart – The Neighborhood Clusters that make up the Sandtown and Federal Hill neighborhood groups.

For this research I purposefully chose two demographically distinct neighborhoods. I felt that these two neighborhoods would reveal more striking differences in trends than looking at the whole of Baltimore City. The choice of neighborhoods also tried to retain similarities in size (area in square miles), housing stock and style, as well as geographic features.

I chose a cluster of neighborhoods in Federal Hill and a second cluster located about a mile north west from there, and areas known as Sandtown-Winchester (Figure 1). The Sandtown-Winchester cluster consists of three separate neighborhoods: Druid Heights, Upton and Sandtown-Winchester. The Federal Hill Cluster is composed of five smaller neighborhoods: Sharp-Leadenhall, SBIC (South Baltimore Improvement Committee), Riverside, Federal Hill, and Otterbein. Spatially each area measures 0.79 sq. miles for the Sandtown-Winchester and 0.74 for the Federal Hill space. Major thoroughfares bound Sandtown on each side, and by Druid Hill Park to the north, in the same way Federal Hill is surrounded by major roads bringing traffic in and out of Baltimore, and by the Inner Harbor to its immediate east.

Neighborhood Study Sites:
Sandtown-Winchester and Federal Hill Clusters,
Baltimore City, MD

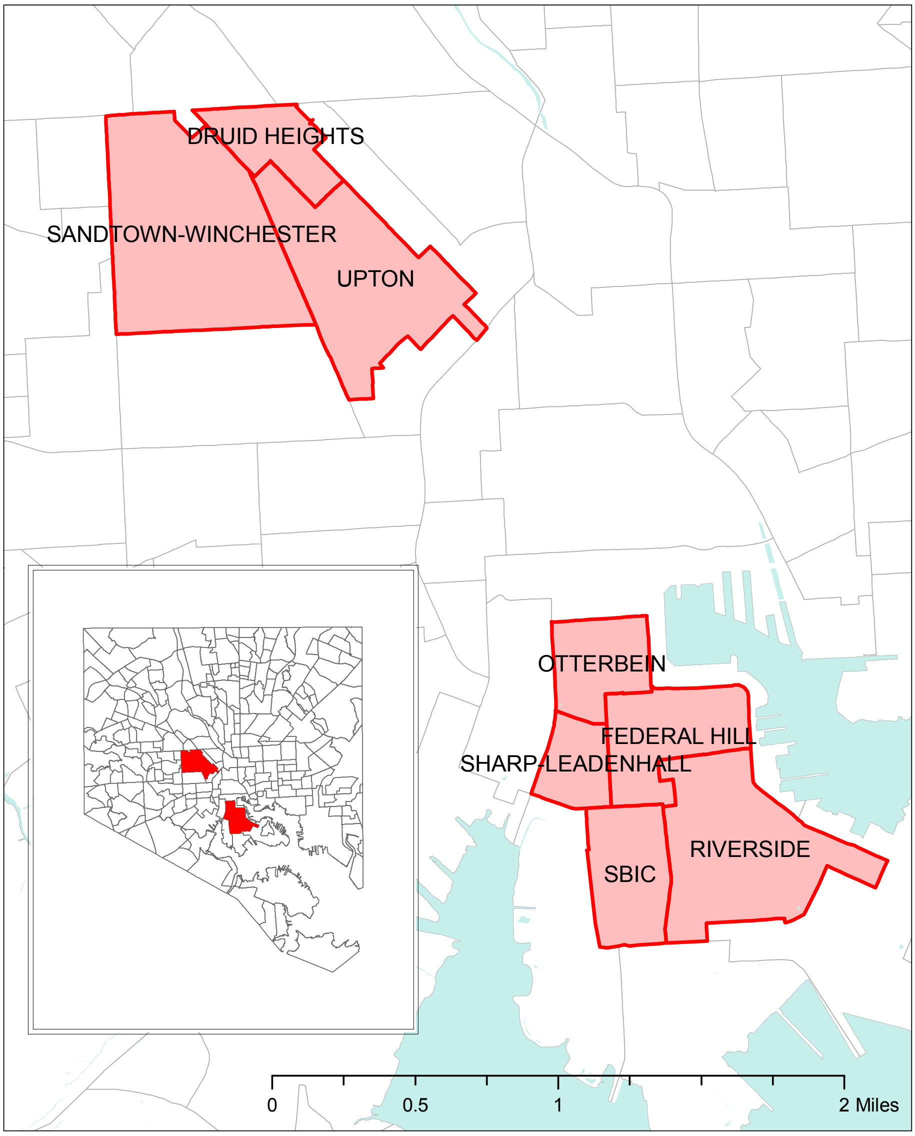

Figure 1 - Neighborhood Study Sites: Sandtown-Winchester and Federal Hill

Neighborhood study sites, - Sandtown-Winchester (Druid Heights, Upton, and Sandtown-Winchester) and Federal Hill (Otterbein, Federal Hill, Sharp-Leadenhall, SBIC and Riverside), in Baltimore, MD showing their relative location to one another.

The selection of neighborhoods was also governed geographically by an attempt to choose lived-in spaces that were relatively contained and uninterrupted by major topographical features, such as highways, rivers, rail lines etc. Both neighborhoods feature large city attractions with Druid Hill Park in the north and the Inner Harbor to the south. These features not only bring tourists and foot traffic, but they also constrain the geography of people and their movements through and about their neighborhood spaces. Both neighborhoods conform then as relatively uninterrupted space; the Sandtown-Winchester area bounded roughly by North Avenue, Pennsylvania and Fremont on the east side, West Fayette on the south, and Bentalou Avenue on the west, while the Federal Hill cluster of neighborhoods are bounded by Key Highway on the north and east, Wells St. on the south and Leadenhall to the west.

Housing stock is also similar in size, imprint and density in both locales. From the omnipresent, and smaller footprint of the traditional Baltimore style row home to larger, Queen Anne period houses in Marble Hill in Upton (in the Sandtown-Winchester cluster), to again larger architectures of Federal and Greek Revival styled homes in the Federal Hill group there are few “high density” high-rises or apartment buildings in these spaces. Yet, population density is <u>not</u> expected to be similar because, for example, the number of vacant properties is expected to be much higher in one neighborhood group. It is the demographics of the lived in space itself that is expected to differ the most here, while being able to “hold constant” the physical attributes. While the two spaces are different socially, like most city spaces, they share intertwined pasts that make them what they are and are not today.

Urban Renewal…But for Whom?

As early as 1792 the Federal Hill area of Baltimore had been under development (Hayward and Shivers 2004). Increased interest by speculators and merchants stoked the building of brick row houses in the area starting at the turn of the 18th century. The abundance of brick row houses in Baltimore came about through new fire ordinances, laid down in 1799, and the practical abundance of material for bricks as building material (Ibid). Many of these new homes were reduced in cost through the application of "ground rent"; while you bought the home, the land was leased to you, typically for ninety-nine years. Hayward and Shivers point out that early Baltimore landowners were keen on building as many of these as possible. Increased immigration into Baltimore during the 1850's increased demand for still smaller brick row houses. Many of these smaller versions were added to city housing stock, particularly in neighborhoods in west Baltimore and Federal Hill. Here the Baltimore-Ohio Railroad met newly-arrived immigrants at the dock as they stepped off steam ships from Europe (Everett 2006); large numbers chose Baltimore's port for its direct path into the country's interior (Scharf 1881). Today the legacy of that speculative real estate model, and its building practices, continues to shape social interaction in communities all across Baltimore.

The geographic nature of Baltimore's harbor, an extension of the inland reaching water of the Chesapeake Bay, far inland from the ocean, made for a natural port and overtime and became closely intertwined with industry and shipping. From points east in Canton the piers and factories wrapped along the twisting water's edge all the way west and south to Federal Hill's docks. There, at Montgomery Street, all manner of seafood and produce arrived daily. Oysters, crabs and other seafood were brought ashore by local waterman and delivered to the numerous canneries located here, and all along the Baltimore harbor waterfront. The canneries processed not only seafood but also fresh farm produce as it arrived daily by rail from farms and orchards outside the city. The city's inner harbor area became a unique transportation hub providing access to points east, up and down the eastern seaboard and abroad to Europe, while feeding the interior manufacturing and urban centers to the west, making it an important and vibrant manufacturing and transportation center until the pre-World War II era (Scharf 1881). Baltimore's harbor however was not a "deep water" port and eventually was unable to handle all but the smallest of the newer transportation vessels. The last major passenger vessels ceased to use the port after the 1940s (Maryland Dept. of Planning, 1993) and this, combined with manufacturing losses that followed through the 1980's, sealed the fate of the Inner Harbor. In 1983-84 the harbor lost its Western Electric and Bethlehem Steel plants, and with them almost 6000 jobs. The punishing economy closed out almost thirty years of nothing but decline where decay reigned as warehouses went abandoned and the space about them became increasingly dilapidated, undesirable to visit, and unsafe. Nothing remained but the "rotting piers (to) testify to Baltimore's decline from a once-powerful port and manufacturing city" (Fee and Shopes 1991, 241).

Racial Segregation and Urban Renewal.

Jim Crow laws that dictated where blacks could or could not live in Baltimore City, segregating blacks from whites, were struck down in the 1940's, but segregation persisted. In a 1943 Baltimore Sun newspaper article, the author notes that blacks had nowhere to live but the "Negro Archipelagoes". It was among these islands that one fifth of the city's Black population was found huddled onto only one fiftieth of the city’s total land area. One of the worst overcrowded and isolated neighborhoods was the Sharp-Leadenhall neighborhood located in the southwest area of Federal Hill (Hayward and Belfoure 2001). The civil rights movement pushed for the dismantling of these bulwarked communities, as well as laws and covenants that prevented Blacks from living in neighborhoods otherwise open only to Whites at the time (see for example Hurd v. Hodge, 334 U.S. 24, District of Columbia, 1948). Segregated communities suffered in some of the worst economic, health and social conditions in the country. Baltimore, recognizing that crushing poverty was having on the physical and social spaces of the city, embarked on its first urban renewal plan in 1951 when it launched the “Pilot Area” neighborhood revitalization project in the Mt. Vernon area of the city (Millspaugh and Breckenfeld 1960). While it met with mixed success, it laid the foundation for future renewal projects.

Urban renewal officially came to Federal Hill as part of the Inner Harbor redevelopment projects under the David Wallace Plan of 1963 (Warren and McCarthy 2002). The major initiative followed the successful redevelopment program of Charles Center, located just above the harbor, spearheaded by then mayor Theodore McKeldin. McKeldin’s new plan spanned from Canton in the East to Federal Hill in the West and made explicit how buildings would be designed, placed, and used (Hayward and Shivers 2004). The Wallace Plan set the stage for the Federal Hill area’s growth and even survival through the worst of the economic downturn that arrived in the following decades after its implementation. Through the 1960s and 1970s, it provided proof positive that urban revitalization and reinvestments can affect adjacent neighborhoods as Federal Hill continued to grow while other locales in the city remained stagnant and even decayed. At the same time the struggles between old and new Federal Hill were also laid bare when it was announced, as part of the renewal plan, that all of Otterbein, the northern neighborhood in Federal Hill, was to be razed for space for a signature architectural building. Public outcry by local residents forced the city to reconsider and ultimately the city decided against the demolitions and, instead, auctioned off the vacant houses in the neighborhood with the "$1 Home" program.

Launched in 1971 by Mayor William David Schaefer, the Baltimore Urban Homesteading Program sold tax delinquent properties to new owners for the sum of $1. New owners were only required to bring them up to code (i.e. plumbing, structural, electrical) and then live in them for a minimum of eighteen months. After this time, they were given full legal title to the property. While the program was a measured success - later more than 50% of those homes returned as housing stock and to the city tax rolls - Brambilia (1979) points out that the program's success was mainly with *middleclass* persons who otherwise wouldn't have chosen to live in the city. He specifically notes "the program did not attract the traditional inner-city residents"(Brambilia 1979:83). However, that had been Schaefer's goal all along, to stem the hemorrhaging population and bring residents and business back to Baltimore. It was more of a success with wealthier whites from *outside* the city than it was with poor Black folks who *already* lived here.

In 1979, when Brambilia writes, five hundred homes had been sold for the $1 price. Of those, two hundred and twenty nine were "scatter sited", and notably 108 were in Otterbein, and 125 were in Barre Circle – immediately adjacent, and slightly northwest, of Federal Hill, bordering the neighborhood of Pigtown. In 1986 the program ended, too top heavy with subsidies to be sustained; by then a total of 600 homes had been sold (de Courcy Hinds 1986). Almost *half* of the homes sold were in the immediate vicinity of Federal Hill. Here, largely White outsiders gained almost immediate and completely paid homeownership in a matter or years in a space highly subsidized and supported politically, socially and economically by the City of Baltimore. Rebuilt and reorganized Otterbein and Barre Circle are today some of the most expensive addresses found in all of Baltimore City. Arguably, this almost instantaneous wealth generation radically shaped the fortunes of these particular neighborhoods. Furthermore, the cultures of those spaces have not developed along the usual, or "natural" trajectories: most neighborhoods might take over decades of change, through cycles of decline and development. When the "$1 Home" program ended in 1986 *forty thousand* people remained on the city's public housing waiting list (Ibid). While Federal Hill-centric development has continued (Canton and South Baltimore developments being current examples) such urban programs don't serve those that need it most (Combat Poverty Agency, 1996).

During the 1970s and 80s, The Wallace Plan did help neighborhoods adjacent to the harbor weather the loss of heavy manufacturing. Inner harbor ports moved from the downtown area to the deep-water terminals located in East Baltimore and Dundalk. The Wallace Plan focused on building the area as a tourist draw by opening the Maryland Science Center in 1976 (located immediately north of Federal Hill) and Harborplace shopping center and mall in 1980. The National Aquarium opened in 1981 and cemented the Inner Harbor/Federal Hill space as the draw it is today for both tourists and many affluent city residents alike. At the same time Federal Hill began to turn the corner economically and socially as massive infrastructure and investment in the Inner Harbor had spillover effects. Housing values *increased* during the 1990's economic *downturn* (Hayward and Belfoure 2001) and since the 1990's, and through the 2000's, the area has become a magnet for young, urban, and largely white professionals who have invested in and rehabilitated much of the housing stock there.

Keeping Up Neighborhood Appearances: Class Stigma and Formstone. Gentrification moves a symbolic step further when we consider the removal of the Baltimore-ubiquitous "formstone" that covers many brick row homes in Federal Hill, and other still working class, neighborhoods in the city, like Highlandtown, Canton, and South Baltimore. Feelings on its architectural worth are decidedly strong – some having called it an architectural plague (Sherwood and Remsberg 1995) while John Waters, Baltimore filmmaker, has called it the "polyester of brick"(Jensen 1998). Invented in Baltimore, by Albert Knight in 1932, this faux stone masonry was concocted to unify the look of the new suburban homes, not necessarily for city homes. Yet, unexpectedly, it was a hit in Baltimore City, particularly in the working class neighborhoods of immigrants in the eastern neighborhoods. That it found its way onto more working class homes than better off ones was no accident. These poorer neighborhood row homes, built decades earlier by land speculators, were often built with the cheapest of building materials, and in particular more porous brick that was prone to leaking and degradation. Formstone applied was, for these homeowners, a practical, repair decision, not necessarily one of aesthetics (Hayward and Belfoure 2001). Especially through the 1950s and 1960s, it was applied to tens of thousands of once red brick row homes found in Highlandtown, Pigtown, Mount Clare Junction, and elsewhere, including Federal Hill. However, the practical application had the unintended consequence of signifying the class of a neighborhood's residents, namely indicating poor, white, and working class. As urban renewal progressed in Baltimore neighborhoods, formstone took on the role of "social indicator" as well; it became an indicator of neighborhood health and revitalization. Those neighborhoods with formstone remaining tended to be older, more working class, and longer-term homeowners, while spaces where it was being removed indicated a neighborhood undergoing revitalization. (Ibid).

As symbol representing one's social status and class, one of the first renovation projects of any Federal Hill "fixer upper" was the removal of *any* formstone. This fake stone says so much, it resonates so deeply, about the working class history of a neighborhood and its residents that it *must* be removed to distance one's self from the class it represents to other Baltimoreans. The original brick, in contrast, speaks for the identities of the *new*, urban professional residents in these spaces. The "true" old neighborhood is supplanted with a *new* vision of "neighborhood", with norms consistent with the new urban pioneer living an "up and coming" neighborhood.

Uncertain Futures – Neighborhood Change and Norm Conflict in Federal Hill

The neighborhoods of Federal Hill remain indebted to, indeed embedded in, the history and contributions of the working class residents that came before them – and in that lays a tension between past and present for the Federal Hill area. Many earlier-settled residents still occupy the peripheral neighborhoods of this space: especially SOBO (South Baltimore), to the south, and Sharp-Leadenhall, to the west. The latter finds itself sandwiched between the newly gentrified Federal Hill proper, on the east, and new sports stadiums built in the 1990s on their west. The future plans and trajectories of this area are largely displacing these last working class bastions. The designation of spaces like Federal Hill as "historic districts" increases property values and taxes, but it also forces others to leave who cannot afford to live there any longer (Hayward and Belfoure 2001). Newer, tonier residents, like Jenna Bush, President George W. Bush's daughter, and the longtime "locals" do not always live amicably as neighbors. The noisy, drunken hoots and hollering from working class patrons just let out from their neighborhood corner bars do not always mix well with the newer residents sitting atop their rooftop patios looking down, literally and figuratively on some of their neighbors below.

In the thirty years since the first neighborhood redevelopment projects there, tremendous change has occurred. To the east of Federal Hill Park, where once working class men and women labored on the docks and wharves, *The Ritz Carlton's* million dollar condominium town homes now grace the waterside. To the north, Schaefer's $1 homes of Otterbein now sell at a median value of $250,000 with many pushing a half million dollars or more (zillow.com) while real estate in Federal Hill proper pushes the million dollar mark regularly. Entertainment mega-structures, like the baseball and football stadiums to the west, flank the rest of the neighborhood bringing throngs of visitors, tourists and local Baltimoreans to the area regularly.

The city's constant attention and investment in the adjacent businesses, transportation and entertainment structures feeding the Inner Harbor area, even more so now than ever before, continue to spill over with positive results for the area. Federal Hill persists as the city's most sought-after addresses. It is considered to be (by and large) safe, clean, and filled with well-kept homes populated by well-heeled residents. Tony streets are filled with trendy shopping boutiques, top-notch restaurants and a general sense of life beyond the incivilities that plague much of Baltimore. It is these *residents*, these "urban pioneers" that purchased and rehabbed these $1 homes some time ago, who might be considered the largest beneficiaries. In a time span unheard of in most communities, a few decades at most, they profited from a level of wealth generation for the community and themselves that has truly transformed this space, economically, politically and socially. Nevertheless, Federal Hill has not cemented its reputation as "*the* neighborhood" to live in just yet. Friction between its older, working class, residents still on living on the periphery threatens the idyllic nature of the space as new "urban professionals" vie against the "locals" to maintain control over the direction their neighborhood is headed.

Sandtown-Winchester – Soldiering Forward Against the Odds.

About a mile to the northwest of Federal Hill, but a world away socially and economically, lay the three neighborhoods comprising the Sandtown-Winchester group in this study: Druid Heights, Sandtown-Winchester proper, and Upton. Formed in the early 1800s, the Sandtown-Winchester neighborhood name is derived from the sand quarries that existed in the area and after General George Winchester, the president of the Baltimore and Susquehanna Railroad (Baugher et al. 2007). It was, and largely remains, one of the most concentrated and historically significant Black neighborhood in Baltimore (Hayward and Belfoure 2001).

The Sandtown-Winchester area is one part of the city where blacks were "allowed" to live while legal segregation was still in effect. Yet, economic, political and social circumstances also basically imprisoned blacks in this space after desegregation began in the mid-twentieth century(Hayward and Belfoure 2001). Birthplace and home of Supreme Court Judge Thurgood Marshall, and jazz legends Billie Holiday, Cab Calloway, the area is home to 40 plus African American and other churches and has a deep history of culture and “firsts” for the city. The 1920s saw grand vaudeville theater at the Regent Theater. Later renamed The Royal in 1929, it hosted the first talking movie shown in Baltimore (SHHA 2006).

Through the 1930s to the 1960s Baltimore’s black population grew dramatically from 142,000 to 326, 000 (SHHA 2006). At the same time, more than 440,000 whites fled to the suburbs, encouraged by block busting, zoning (redlining) and school busing programs(Orser 1994). Fueled by Jim Crow laws and the exodus of blacks from The South, Baltimore experienced increased migration to already highly concentrated and impoverished black neighborhoods. To add to the misery of tenements was the difficulty in finding work and making ends meet. Baltimore continued to lose population through the 1990s as middle class blacks joined whites leaving the city. In 1950 Baltimore’s population was 950,000; by 2006 it was 631,000 (Clinch 2008); it is still in decline today, most recently measured as 621,000 (2010 Census).

In the 19th century, industry connected Federal Hill neighbors in the south to Sandtown in the north. The B&O Railroad terminus was located in Federal Hill. The rails wound northward, connecting with the Maryland and Baltimore and Potomac Railroads at a freight depot located on Fulton Ave. Here, “Arabbers”, the horse-pulled fruit and vegetable, and fish carts that began traversing many African American neighborhoods in the city of Baltimore in the early 20th century, could pick up produce and begin their daily rounds. Today, Sandtown-Winchester remains the home of some of the last Arabbers in the city. (Baugher et al. 2007). Like Arabbers, many of the area inhabitants in Sandtown were common laborers, largely shut out of higher paying industrial line positions, until mid-century changes in Jim Crow laws desegregated the workplace (Smith and Smith 2009).

In the 1970s, Baltimore's mostly black population outpaced national averages in poverty and unemployment (Liebel 2006). In 1979, black youth employment was over fifty percent (Ibid). By 2004 Baltimore had lost over a third of its population; seventy-five percent of all manufacturing jobs disappeared and with them 100,000 work positions (Ibid). Smith and Smith note how population decline and job loss contributed to the decline of urban space – in this case historically black neighborhoods – that made them "ripe for various forms of crime and the creation of various underworld economies, legal and illegal" (2009, 84). The Sandtown-Winchester area was just such a black space and was ravaged by these social and economic losses as crime, blight and addiction took a firm and unforgiving hold of their neighborhood.

The 1960s and 1970s brought hard times for many U.S. urban communities, including those in Baltimore City. Funding for community organization under the Nixon administration decreased and then ceased altogether (Brambilia 1979). In 1968, riots followed the assassination of Dr. Martin Luther King, leaving six dead and 5000 arrested. Following the unrest, Baltimore took steps to address the social inequality and marginalization it saw in its neighborhoods. The Baltimore City Fairs, launched in the 1960s and carried on through the 1970s, specifically targeted pride of one's neighborhood, its culture and institutions as a way to overcome the balkanization that had hurt so many urban neighborhoods (Fee and Shopes 1991). While well-intentioned and attended, the fairs were still held at Charles Center, and later at the Inner Harbor – both locations that were far away from the reality and strife most African American communities were experiencing in their own neighborhoods. Working against economic headwinds these communities were then dealt an additional blow with the arrival of crack cocaine and widespread heroin distribution in the mid-1980s. Rather than move forward many urban communities, already on the brink economically, stagnated and reeled under these combined assaults. As such, many urban spaces, and in this case black neighborhoods, descended into almost unimaginable decay through the 1980s.

By 1986 the population of Sandtown-Winchester had plummeted from 40,000 residents to just 10,000 persons. Unemployment hovered at 50% while one in every four houses was abandoned and in decay (SHHA 2006). Two years after he became Baltimore's first Black mayor, Kurt Schmoke stepped in with a revitalization effort for the area. In the late 1980s, to address the area's catastrophic state, the city partnered with James Rouse's Enterprise Foundation[3] (Hayward and Belfoure 2001)

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[3] James Rouse was an influential civic advocate instrumental in Baltimore City's earliest renewal efforts. He guided key urban housing hygiene programs in the City administration in the 1930's and 40's and was the chief architect of Baltimore's first urban renewal plan in 1951. He continued through the1980's as the successful planner and architect of Baltimore's Inner Harbor. Internationally renowned for his utopian urban planning vision – the town of Columbia, MD being his signature urban imprint perhaps - he is not without detractors and critics of a style some feel promotes artificiality and consumption rather than a "real" sense of neighborhood. Baltimore's Inner Harbor is just such a

to develop a comprehensive, neighborhood-wide, renewal plan. Rouse believed that "intervention into the physical environment holds the key for social regeneration" (Gillette 2010, 96) and this fueled his urban planning, development and renewal ideals. However, the results of the Sandtown-Winchester project were mixed.

Most of the $60 million spent there went into "brick and mortar" projects. The project demolished and then rebuilt hundreds of homes. However well intentioned, it built far more housing than the current population density could support after so much neighborhood flight had already happened. The economics of the 1980's, coupled with the social strife of drug use and rampant crime in the area, further conspired to prevent the homes from ever becoming *affordable* for the local residents. Furthermore, without political organization and leadership skills, development benefitting residents never got off the ground (Yeoman 1998).

Addressing the project's failures the Sandtown Habitat Homeowners Association has engaged in a more holistic approach to community building – moving from brick and mortar to rebuilding the *social* fabric that knits its neighborhood together. Defiant of naysayers the Sandtown Habitat Homeowners Association website declares:

> So to those who would say there are no signs of life in this "outer harbor" neighborhood...the members of the Sandtown Habitat Homeowners Association respectfully submit our existence in dissent of your observation. For we are indeed alive, and have every intention of claiming our rightful place at the "inner harbor" banquet, we just haven't finish cooking our portion of the meal yet.(SHHA 2006)

"consumption space". See, for example, Bloom, Nicholas Dagen. 2004. *Merchant of Illusion : James Rouse, American's Salesman of the Businessman's Utopia*. Columbus: Ohio State University Press.

Their sense of disdain for those who emphasize the "Inner Harbor" as the only neighborhood worth valuing is palpable, as is their sense of abandonment. Nevertheless, they soldier on. Drawing on local Black churches, Habitat for Humanity and other non-profits they are working to emphasize the integration of residents back into the city spotlight as a location of neighborhood pride rather than a space to avoid(SHHA 2006). The homeowner's association recognizes the area is replete with examples of historical continuity, as well as social and cultural cohesion, not just decay. Even if outsiders can't see past the abandoned buildings, prostitutes, crack dealings and general incivilities the worst "urban ghetto" seems to serve up, these residents and their credo remind us that even the most devastated communities retain at their core, amazing resilience and strengths – and, importantly, a sense of community even at the worst of times.

Data: Descriptions, Definitions, and Cleaning

Calls for Service vs. Events

A key variable in my analysis is "calls for service". It is important to note a distinction between "calls for service" and the "events" those calls seek to remediate. The former is a *request* for action, initiated by a resident to report or resolve some issue or incident (including crime and policing matters). The problem itself is known as an "*event*". Ratcliff specifies: "The term 'event' has become accepted as a way of distinguishing the position of an individual observation within the study area" (Gatrell et al. 1996 in Ratcliffe and McCullagh 1998). An event then is the object of attention that a citizen directs focus on, or action towards, in a process of resolution of that identified problem. In all cases, the assumption remains that these calls were made by residents with a reasonable expectation that a) the city would work to remediate them for their neighborhood, and b) that the calling action itself is an informal social control mechanism a resident would use to effect either *behavioral or environmental change* in their own neighborhoods.

I do not concern myself in this research with the verifiability of the event a caller has called about. Since the focus of the project is whether or not residents find themselves calling about particular problems it is the action of "calling" that matters, not whether or not the caller was correct in assessing the event itself[4]. Call center operators themselves do not verify the call but are trained to create actionable items so it is reasonable to expect a call represents what it is coded to represent.

Deriving The Three Dependent Variables from the 311 and 911 Call Universe

The City of Baltimore's "One Call Center" manages both 311 (non-emergency) and 911 (fire and police emergency) calls from residents and businesses alike. In 2008 the Center managed 262,353 separate calls for service requests, organized into 95 specific city agency categories, or roughly a quarter of a million non-emergency (311) requests for service each year. Calls for service are assigned to the city agency responsible for executing its resolution. While the city recently made it possible to

[4] One other issue is duplicate calls for the same event, made by the same resident. Or, in a worst case scenario, all calls for all issues made by a few or one resident in a neighborhood. Personal experience has shown that use of the call system in Baltimore is quite dispersed amongst local residents. That said the motivations for some to call about some kinds issues, while disregarding others, remains a data problem to consider.

enter "requests for service" online the data set excluded this method of call entry. I include only calls made by telephone.

I requested the last three years of available data from this system for use, specifically from fall 2006 through the fall of 2009. The cut-off date of fall 2009 was chosen because, as of that date, major changes in the availability of the telephone service changed from a 24-hour/day, full-access system, to one with restricted hours. In addition, a major advertising campaign meant to encourage citizens to use the 311-service system ended in 2006; thus 2006 was chosen to mark the earliest data point. Fall-to-Fall periods were chosen in an attempt to lessen variability in seasonality of call patterns (i.e. do they vary according to type of needs because of weather – clearly some will). For the purposes of simplification, the 95 categories used were condensed into sub-categories, deduced by common themes, as follows:

- Animal Control (strays, abuse, sanitation, dead animal pick up)
- Trash and Refuse (including litter, alley and street cleaning, illegal dumping, graffiti removal)
- Housing violations (trash, weeds, construction without permit, overcrowding, structural deficiencies, rodent and insect infestation, vacant houses)
- Recreation and Green spaces (dead trees, park and pools, ball fields, and playground maintenance, grass mowing of public properties)
- Citizen Assistance Services (requests for emergency service telephone numbers, illegal distribution of flyers, home weatherization assistance)

- Parking (parking without permit, parking meter complaints, abandoned vehicles)
- Health (Rats, bedbugs, smoking initiatives, food service sanitation complaints, potable water investigation
- Water and Sewage (water main breaks, in-home sewage back-up, storm drain maintenance, open hydrant)
- Streets & Sidewalks (cracked, broken, potholes, steel plate complaint, traffic signs missing/repair/replace, crosswalk maintenance)

I condensed the Calls for Service (CFS) into three larger call groups to simplify analysis: physical disorder, social disorder and emergency social disorder calls. Calls were subcategorized depending on calls the target problem area (a physical environment versus social behavioral issue) and depending on whether the issue was non-emergency or emergency in nature:

1. Physical Disorder Calls: Calls for issues like pothole repair, streetlights burned out, or graffiti removal from a building. In each case the resident worked to effect change on their *physical* environment. In the analyses these are referred to as 311 Physical Disorder calls for service (and abbreviated as 311PD).
2. Social Disorder Calls: These were calls made in response to issues residents considered "incivilities", that is the *behaviors* of their fellow residents. These calls are identified as 311 Social Disorder calls (in some places as 311SD).

3. 911 Social Disorder Calls. These were calls made about emergency social disorder issues that were in need of immediate action by authorities. In these calls the resident caller identified some action or situation that, given its seriousness, as well as its perceived criminal nature and threat to personhood, objects or environment, required immediate redress and attention by *police*, rather than any other city agency. These calls for services then are noted as 911 Social Disorder Calls (and 911SD calls in some places.)

The last two data sets are distinguished from one another. Where the former identifies actions by citizens that represent violations of city code they are not necessarily *criminal* in nature, nor does they require immediate redress. Instead they represent violations of city code (e.g. littering) and/or personal or normative values (e.g. residents making loud noises). Calls of this nature include pet abuse, complaining someone's child is truant from school, or identifying a resident who places trash out in plastic bags, rather than the mandated metal receptacles. On the other hand, 911SD calls represent issues identified as criminal and in need of *immediate* action by *police* – not a city agency. This contrasts sharply with 311 *non-emergency* social disorder calls where corrective action is generally expected between 3 and 14 days. The table below (Table 1) illustrates the three-call type categories and, within each, the constitutive call types used to create each category.

Cleaning the Calls for Service Data

"Calls for service" included in the data analysis, and later in OLS and GWR models, were limited to those made by citizens who I assume, had a reasonable expectation that doing so would have a positive effect on their immediate, neighborhood and its social or physical environment. Within the dataset there were calls made to 311 services that I interpreted as strictly self-serving; calls where and individual was seeking resolution to a problem where only they, not a larger group or community, would benefit. On the other hand, there are calls made with the intent to enhance "the greater good". For example, if a resident calls for "Bulk Trash" pickup of an old refrigerator they do so they can remove it from their <u>own</u> home. Such actions benefit neighbors or neighborhood little, if at all. However, when a citizen witnesses *dumping* of a refrigerator into an alley and then calls the city, reporting "illegal dumping", the citizen has set in motion a reasonable expectation that a) the city will respond to their request, and that b) that the request made belongs in a category of unfavorable actions in need of intervention -- and not just by city agencies, *but monitored and enforced locally by residents*. Timely response by the city further validates the residents' actions and encourages them to continue to identify violations and to call them in for correction. More broadly put then, calls for service, selected for analysis in this research, reflect issues residents have identified as "public issues" not "private troubles".

From the calls for service database, I excluded those calls where the resident could be assumed to be acting in self-interest primarily. For instance, self-interest is reflected in residents calling 311 and asking Department of Public Works to come and check water in *their* own basement. In addition, persons calling for information about garbage pick-up, the next school holiday etc. are all *self-interest* driven actions. Any such calls were removed from the data set reducing the initial 311-call data number of observations from 1,157,245 to just over 750,000. I also excluded calls made didn't result in impacts on *residents* or their lived-in physical spaces directly. For example, calls about complaints for city employees, requests for information about what day of the week refuse pick up was scheduled, or complaints to the city's General Accounting Office for questions about expenditures within an agency are examples of calls excluded. In the emergency call data base this exclusion practice left out officers and police stopping for gas, out on warrant delivery, calling to say they were on "relief" time (restroom breaks) and so forth. As noted above no attempt was made to remove duplicate calls responding for the same event, as call volume is the primary variable of interest.

All Calls for Service As Condensed Into The Three Call-Types and Demonstrating Call Sub-types Used to Construct Each

Call Type:	311 Calls Made About Physical Disorder	311 Calls Made About Social Disorder	911 Calls Made About Emergency Social Disorder
Sub-types:	Dirty street or alley needs cleaning	Animal at risk/being abused	Noise complaints
	Housing Code violations (incl. grass, trash)	Housing Code violations (occupancy, health)	Juvenile disturbance (incl. loitering)
	Trash and litter at residence/in street	Parking complaints	Suspicious person
	Water complaint/issue/repair request		Discharge of firearm (heard)
	Rodent (rats/mice) control		Narcotics (use on view, drug dealing etc.)
	Street repair (e.g. pothole)		Child at risk or being abused
	Street light out or in need of repair		Vehicular disturbance (Dirtbike riding/racing)
	Animal running at large		Drunk or intoxicated person
	Forestry/tree care		Disorderly person
	Dead animal (in street/alley etc.)		
	Traffic signage and control		
	Recreation and parks issues (grass mowing etc.)		
	Graffiti and visual blights (incl. illegal signage)		

Table 1 - All Calls for Service and where located within the three predictive call-types models predicting Calls for Physical Disorder, Social Disorder and Emergency Social Disorder

Selection and Editing the Spatial Extent of Sites Included in Analyses

As mentioned earlier, a pseudo-grid was laid over Baltimore City's spatial extent, a grid with each square measuring 250' x 250' – or about one city block. The total number of grid cells was roughly 40,000, about 200 x 200 cells laid over the surface of Baltimore City. Each cell inherited the local data values – calls for service rates (the dependent variables) and local census data (the independent variables). Local call rates aggregated *within* each cell then rendered each grid space as a *unique* locale when final analyses were executed – or 40,000 micro-spaces. However this grid approach also creates artifacts along edges of some spaces, e.g., when land and water meet a cell can overlap, containing *both* types of spatial domain. It also created domains that do not contain populations that contribute to the calling rates of interest in this research. Furthermore, the spatial qualities of some cells necessarily required their removal from analyses. For example, non-lived in spaces distort spatial analyses because, when included in predictive models, the GIS is ignorant of those spaces as "non-residential" and processes them normally rather than spaces that might be *barriers* to social diffusion and action. To best approximate the spatial patterns of residents calling about physical and social disorder, and to acknowledge the impact of topography on those response patterns, I excluded the spaces noted below.

After the databases were cleaned of extraneous categories, I also removed entire spatial zones from the citywide plane. Primarily I excluded areas of the city that were predominantly industrial in nature, as well as large parks, large cemeteries and other large spaces like university campuses[5]. The exclusion of these spaces is crucial: they have no acting residents within them. Removing these spaces is essential to correctly calculate local population densities, rates of vacant houses etc. when coupled later with census data; these corrections are commonly *not* executed in traditional, stochastic analyses when census tracts are used with along with aggregate measures. As Cuthbert points out that many empirical studies use zonal data but "(z)onal data are … problematic when estimating (population) densities because extensive unpopulated areas are included in the land-area measurements of the zone" and the zones themselves are usually constructed for *other* purposes, not as catchment areas for any later-assigned data values (Cuthbert and Anderson 2002, 522). To create a more conservative spatial plane edges about water and parks were "nibbled back" by 700'. This was done to lessen the possible impact these spaces themselves have on calling rate outcomes. For example Kuo and Sullivan (2001) note that green spaces are known to influence residents' well- being and the rates of crime events happening to residents in those spaces.

Finally, I excluded census tracts with population counts of zero and tracts with very low population counts (less than 35 persons) when those same spaces registered no calls for service. Given the millions of calls made, all over the city, it was an *extremely* low probability there would be zones with "zero rate" values when *any*

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[5] University campuses were excluded because, while populated, these spaces are self-contained communities with their own facilities and services management. The assumption was students were not about to make calls for issues on campus that city services would need to attend to.

population was present there. These corrections reduced the number of cells for analysis from 40,000 in the grid to about 27,000, a reduction of about 32%.

Decennial Census Data (2000)

In addition to the Calls for Service data demographic and local neighborhood measures were derived from the federal Decennial Census of 2000. While the 2010 Decennial Census data was just being released piecemeal while this research was being completed the required variables were not available. Given the historic social distribution of race and class in Baltimore, and that the auxiliary data represented three years of call data from a period *before* the 2010 Census enumeration, using the 2000 data was not expected to alter the results significantly. From the 2000 Census data I used block level measures on resident demographics (income, race, education, poverty,) as well indicators of local, physical environmental health (vacant homes, numbers of houses owned versus rented) and measures of neighborhood social disorder, including a resident's length of time there, percent of residents reporting to be "foreign born", unemployment and local population density to construct independent variables predicting calling patterns. These variables were included to permit analyses of mediating and moderating influences on call volumes, at the two chosen sites of interest where the calls for service were geo-located along with the residents' census data and comparisons made to determine if demographics affected calling patterns and if particular kinds of physical environments or social statuses predicted each of the different calls for service types. Institutionalized persons, including college and university students and corrections and the incarcerated, were excluded from population estimates for local calculations since these persons either a) rely on local, institutional mechanisms to solve problems, b) are transient residents and not wedded to those spaces like full residents, and/or c) were legally disenfranchised from the responsibility or opportunity to exert changes in those local spaces. Finally, using the census data, all calls for service rates were adjusted by local population density measures and then changed from raw call volume rates to population-adjusted rates.

Data Transformations

Creating Uniform Spatial Resolutions for Model Variables

The data I am using comes from several sources, each with different spatial resolutions (i.e. Census data is at a tract/block level, while calls for service/events are "point" data (address specific) at the individual block level. Data need to be at the same spatial resolution in order to perform some of the research project analyses within ArcGIS – the software analysis framework. I transformed data then when necessary to create the same spatial resolutions that could subsequently be overlaid, one over the other. I have already spoken extensively, above, about the use of kriging as the method to create "event surfaces" and outline here the steps used in that transformation process. For clarity's sake I describe the function once, but the same function was used for any data used and created new, uniform resolutions throughout each variable being employed, as "feature layers" used in ArcGIS for the subsequent geographically weighted regression analyses[6]

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[6] ArcGIS uses event or theme "feature layers" as part of its analysis and data manipulation interface. A "layer" can be thought of as a data container – containing the image generated of those data points or polygons on a map – but importantly also a database in the "background". The database accordingly

The variable data set was first imported into ArcGIS, the spatial software analysis tool, and the information geocoded in the case of calls for service data. The observations were assigned locations in space using a coordinate system that enables the analysis of the data according to their geo-referenced data values. ArcGIS provides different models as databases for data storage as it is brought into its framework. Initially data entered the program as "vector data" ("polygons" i.e. bounded areas, census tracts) and "points" (addressed cases) but are ultimately transformed, as part of the data resolution equalization step, into what is known as a *raster* layer database in the GIS.

A raster database model, in GIS, is the second type of primary database containers found in a GIS. It is the world written as if overlaid with a grid of cells. There each cell has a fixed address (located at on an x by y grid of possible cells) allowing each cell to be located in that space. The addressing permits the GIS to co-locate other raster layers "above" and "below" it sharing data from each layer as it *perfectly* aligns with those other raster layers on the z, or layered, axis.[7]. Each raster cell contains one value of the variable measured where that value is a code, or some real number, that represents information about that grid cell area in the "real world". For example, a

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can be subjected to all the usual manipulations as any database, including queries, transformations and functions *between other layers* to generate new data.

[7] In a GIS maps are made of "layers" and so there can be as many layers as there are variables – each with its own database. So a raster "layer" might be one of many such layers, but while the variable might be different, so long as the cell sizes of the layers are the same mathematic relational functions may be performed.

raster feature layer derived from events for calls about "rodent control", over a year, could be a grid of cells with a range of numbers, one in each cell, where the cell value indicates the total frequency of "rodent control" calls found within the spatial area that that raster cell corresponds to in the "real world". While rasters are imperfect in terms of the resolutions as they correspond with the "real world" (how large or how small you make a cell captures some cases while excluding others), they *do* provide utility in permitting the execution of mathematical functions *between* the raster map layers. In the final analyses using GWR each layers value for a variable, contained within a raster cell, becomes the input of a regression equation within that 250' square cell, continuing to the one neighboring it, and next to that, and so on, until there are 40,000 some regression equations, one in each cell.

As part of the data transformation at this stage I elected to set the raster cell size as a square with 250 feet on each side. This is roughly half the length of one many Baltimore city neighborhood blocks. After the resolution of the grid to be used is set, the ArcGIS software was instructed to execute mathematical functions on the input feature layer in order to create a new, smoothed raster data surface (discussed above) with each of the variables. The final product, after raster transformation, then is a feature layer of cells (held in a spatial database in the GIS) spread across the space of Baltimore, where each cell, depending on the variable, contains information, information that lines up precisely with the information from other variables, held in corresponding cells above and below it, until all variables are layered in place. Information in a cell could reflect things like call rate, the count or occurrence of some kind of event type, the quality of the local environment as urban or suburban (dummy variables), measures of income (continuous variables), whether houses so located are predominantly rented or owned, local residents as married or not, race coded numerically, etc. Since variable values can be any kind of number (integer, ordinal, coded nominal, interval, and ratio) additional manipulations were executed as needed..

When hypothesizing the interaction between the physical and social environment and calling patterns I attempted to account for the varying impact of different kinds of events and how some might resonate deeper with residents, impacting them more locally and their neighbors than others, while others kinds of events were relatively minor in impact. For example violent crime calls likely impact a neighborhood more, and further across a spatial extent (i.e. spreading fear, worry, stress etc.) than reports about an "abandoned car". While I hoped to adjust and compensate for the temporality of some events -- ones short in duration versus others that were more chronic – this proved too complicated for this project and was excluded at this time. However, differences in impacts of certain events versus others were weighted, differently, more or less, with algebraic decay functions, that reflected those impact differences. Calls for physical disorder were weighted to have the least distance effect, then social disorder events and finally emergency social disorders weighted to have the furthest reach (see semi-variogram modeling below).

Unlike econometric statistical analyses data weighting in spatial analyses is largely a function of the analytic tools themselves. In traditional statistics we look for normality and then weight observations with some kind of mathematical function. In spatial analyses this in incorporated in the transformation steps (i.e. spatial smoothing and kriging [see (Harvey 2008)]) or in final analysis protocols using methods such as

Geographically Weighted Regression (GWR). For example, unlike conventional statistics, spatial analyses assume there is a certain degree of non-stationarity in variable observations; a measure of how variables differ from location to location across and through space *depending on other local observations and their values* (Fotheringham, Brunsdon and Chalrton 1998). Data observations then and are *not* randomly distributed as stochastic statistics demand. GWR uses an statistical technique to compensate for this influence on values and in so doing *spatially weights* observations relative to surrounding values, taking into account those other measures influence on that one measure. GWR does not, contrary to traditional statistics, weight observations and *then* do analyses on them. Instead weighting is a function of, it is part and parcel of, the execution of the GWR statistical function itself.

To create the smoothed event surfaces (mentioned above) the weighting function starts at "Observation 1". Around that the GIS "draws" a circle, or window, with the observation at its center, and the windows bounds determined using a theoretically sound and statistically determined bandwidth[8] which represents the distance or threshold at which that event's value decays in influence over any other neighboring observation points and their own values. The point density of all observations within that circle's area are computed and observations located nearer to the original observation (the center of that window) are weighted more in their influence on it,

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[8] Bandwidth here is adjusted based on a scale of resolution – how far "out" (away) from the center of an event point might we consider its influence to be compared to other event types. Bandwidth is admittedly arbitrary to some degree, but still is based on theoretical expectations of the impact of events.

while those located at distances further out are weighted less influential. The window becomes a “moving window” that marches across the *entire spatial* plane of *all* observations, stopping at each, using the window, calculating local influence on observation values, then moving on to the next observation, and so on, until all observations have been so centered, and their neighbors been weighted. The output generated is the smoothed, interpolated and weighted set of observations placed into each raster *cell*. These cell values are determined not only by the counts and averages of observations within that immediate cell, but *also* using the *values nearby, at a decaying function of weighting,* using observations *adjacent* and *nearby* (depending on the chosen bandwidth) to determine more accurately what values are through out that space and what they *ought to be* where there are no observations. Where cell values had no observations or values these were then given interpolated values – expected likelihood measures – which provided a smooth surface of *expected* observations that were geographically specific, and permitted the final predictive analysis across the entire surface, even when values had been unobserved, missing, or even skewed by poor data collection and local spatial influences on those values.

Data Transformations to Avoid Problems of the Ecological Fallacy

Ecological fallacy is the assumption a statistical measure made at one spatial level of resolution applies to a more detailed level(Harvey 2008). For example, a measure of poverty concentration, made at the census tract level, does not necessarily mean a neighborhood block would have that same concentration level. This project used “calls for service”, where each call was represented by a “point” geographically addressed to a location. Importantly point data is not *aggregated* data. This is important because aggregate data generates errors directly related to *ecological* *fallacy* - aggregated income data a census tract might lead to erroneous attributions with that data while those results obscure the *individually* reported incomes in that data space, or at the least, more localized patterns. One cannot simply *average* case variable values together, in a census tract, and gain a full understanding of the spatial associations *within* that tract.

Finally the ecological fallacy tells us one cannot make inferences at any scale smaller than the aggregate unit of analysis we first begin with. Accordingly, this research employs methods that can better compensate for the *spatial distribution* of data to permit more accurate prediction of relationships between cases and variables. Point data (in this case as calls for services, each individually addressed in space) overcomes the problems presented by the ecological fallacy because the uncertainty of the data, at any local resolution, is vastly decreased and control over deciding what the level will be, in the first place, is increased while point data can also be used to interpolate *missing data points* with a high degree of statistical accuracy creating what are known as event *surfaces*.

Compensating For Missing Values Using Spatial Interpolation - Creating Calls for Service and Dependent Variable "Event Surfaces"

All data sets are imperfect and need to be assessed for issues of normality of distribution of observations and corrected, weighted sometimes, for observations that are either overly influential or altogether missing. Spatial data – data with some element that addresses or connects an observation in space – requires the same assessment, but with different underlying assumptions about the normality of distribution of the variables in space and their effect on the measured values at other locations.

Spatial data is depicted in maps using three kinds of data formats (Berke 2004). First the data can be represented as points - measurements at a particular location are assigned an icon denoting the presence of that observed variable. Often the point or icon is colored differently from location to location, using some metric of the variable of interest. Second maps might display spatial data as aggregated to some area, usually some administrative boundary like a census tract, into what is known as a chloropleth map. In this depiction different zones are colored differently to represent differences in the variable within each of those spatial domains. One weakness of this method is the application of ecological fallacy, which ascribes the measure found across that entire space, not allowing for local variations to be seen. Thirdly, spatial data can be displayed as isopleths -- geostatistically determined “event surfaces” which illustrate smooth, or continuous surfaces of data variation, across space, much like those seen for temperature gradients on weather maps, for example. There are *predicted* values available at all locations, even points where data remained unobserved or unrecorded, such that *every* location across the spatial plane now contains data points.

This research used calls for service as identified and geocoded points, addressed to specific, locations, across the city of Baltimore. Such a map is useful in depicting the spatial locations of calls themselves, it is descriptive, but it only represents calls that were made – not the likelihood that calls *could* have been made at locations *between those points,* where no data exists or was not recorded. In the example of modeling disease patterns Berke (2004) points out that we are not only interested in describing or identifying locations of disease as reported at specific locations, but we also want to know the *risk* of that disease occurring in the interstitial spaces *between* the observed case reports. While Berke is discussing disease modeling the same theory applies to this research. Here I determine the risk, or better put the likelihood, a citizen will or will not call given their spatial environment – it is the "epidemiology" then of calling behavior. A map using point data, as a spatial representation of calls scattered across the city, cannot accomplish this. Secondly, while chloropleth maps (these are the commonly used maps where census tracts are colored various shades depending on some attribute) can do this, the arbitrary nature of their boundaries (political or geographically drawn) mean risk is applied across that *entire* space regardless of local variations *within* that space. Additionally larger polygonal areas on the maps themselves dominate the visual frame, leading viewers to focus on those areas and not smaller ones (Ibid). An isopleth, an event surface rendering derived from point data, avoids these problems by depicting call data instead as a continuous risk surface. In this way the surface reveals to us spaces that predict the likelihood calls might happen, not only those that *did* happen. Isopleth surfaces are created using the spatial smoothing techniques described as follows.

The interpolation of likely data points – points located between two or more known or given measures - is known in spatial analysis as *kriging* or *kernel estimation* modeling (Harvey 2008). In *Analysing Crime Patterns: Frontiers of Practice* the authors note that kernel estimation modeling is relatively new and that overcomes many of the pitfalls of otherwise aggregated data. It is one of the newest spatial statistical methods being employed to measure crime hot spots given the problems they present with their irregularly shaped areas of density (McLafferty, Williamson and McGuire 2000). Similarly this technique is used here to project "calls for service hotspots" rather than crime, as well as demographic and physical environment hotspots, liberating the data from artificial spatial restraints of census tract boundaries, for example..

Noted above aggregate data used to then identify hot spots is problematic because it cannot account for changes in the size and shape of the bounded area being used as that aggregate unit. Furthermore those areas and shapes, used for the aggregate measurement unit, are ultimately *arbitrary,* even if they follow geography or political boundaries, and are subject to changes by whomever is doing the aggregating at that time (Openshaw 1984). Even more problematic in spatial analyses is the geographic equivalent to ecological fallacy –the Modifiable Areal Unit Problem (MAUP). According to the MAUP, the unit of aggregation, and its *size* (scale), will affect the *numbers of observations* included within any unit size chosen, and so will also affect to, more or less, obscure the spatial relationships and dependencies[9] of the observations included within those boundaries (Haining 2003, Waller and Gotway 2004), However, we avoid these problems when using point-based methods of spatial analyses because working with point features first allows one to interpolate the unknown value of case variables that were unobserved, filling in "gaps" then using nearby observations (Calderón 2009). Interpolation is done as inverse distance weighting is done using a technique called *kriging*. Rather than use traditional

[9] Unlike stochastic measures spatial observations are assumed to <u>not</u> be independent of one another <u>nor</u> normally distributed. Instead certain observations are *expected to cluster* about one another, to different degrees, depending on their attributes. The size of a unit of analysis then would effectively cut out some observations that, perhaps, should be included if unit of aggregation is too small, or include too many, less related, observations, if the unit of aggregation is made too large.

analyses of spatial observations, that use point-based buffers where an area is drawn about a given point to include local observations, while excluding those outside that buffer, kriging employs local and global spatial averaging, taking into account local influences within a global context of expected values. Meersman's work (see Meersman 2005) uses a buffer method but importantly this it is not truly a spatial analysis per se. The initial data *has spatial attributes* but the analyses are not the most nuanced spatial statistical method. Because of the uniform nature of buffer construction often used the zones created are unnatural and even flawed since "irregular" buffers are rarely constructed that reflect the reality of the observations being measured in space (McLafferty, Williamson and McGuire 2000).

I chose then to use kriging as my "spatial smoothing method" to interpolate the point density of observations not seen. For example, the interpolation of calls for service represents an unobserved value as the likelihood of what that rate of calls in a block area *would be* without falling into the trap of the ecological fallacy of ascribing values to a finer resolution area from a larger one. McLafferty et al point out that this method is best suited for "any point set" where observations occur in discrete locations while the likelihood of observations of the same could exist anywhere between them (McLafferty, Williamson and McGuire 2000p. 79-80). For instance, while observations of crime exist at discrete locations the *risk* of crime exists almost *everywhere*. So the density of crime density is modeled as a *spatially continuous* variable – a variable that can be model, viewed, as *a surface* of "peaks" (high crime likelihood) and "valleys" (low crime likelihood) (Ibid , 79) while all along those "elevations" are values that may have otherwise been vacant. This same spatial smoothing method was used in this project for the creation of event "feature layers" –

calls for service about rats, abandoned cars, and so forth. Residents called about particular events (i.e. an abandoned car) and then surfaces were generated from those observed point-based instances to compute interpolated values representing the *likelihood* (i.e. the risk) that a particular environmental event or quality of space (e.g. vacant homes) would exist *between* actual observations.

Kriging, as a spatial smoothing and interpolation technique, is theoretically the best suited methodological transformation for missing data cases (call for service rates, unreported population counts in a block group, etc.) in this project because it avoids misattribution of data and specificity errors that occur as part of ecological fallacy and MAUP problems. At the same time it provides robust estimates for missing data point values. The process for event feature layer creation, required several steps using the ArcView GIS software program described next.

Constructing Map Rate Surfaces Using GIS

The construction of rate and event feature surfaces required the transformation of addressed points of a variable (as a "layer") in ArcGIS (see appendices, page 210) for the specific steps used in the software). The spatial extent of the entire city was turned into a large grid, constructed of 250' x 250' squares as the catchment zones. The 250' square was chosen as a rough estimate of the size of a city block. For each variable a count was made of events (e.g. calls for service made) that occurred within that block. This represented local event *frequency*. Some variables required no correction (e.g. percent black, number of vacant houses, etc.) and remained simple counts or percentages while counts of call frequency were corrected, using the locally measured population, to generate a *rates of calls* at the local level. Each cell center was then assigned a "point" to which the values for each variable were assigned. Picture a grid of squares, a "point" at the center of each square, with a value assigned based on the count or rate for that one variable. Each variable "grid" then has its own "layer" so constructed, an laid over the others – with each point lining up with, the next variable's grid values, and so on. However, some cells in the grid would be absent of values and this is where kriging was used to fill those cells.

ESDA – Exploratory Spatial Data Analysis

Exploratory Spatial Data Analysis, or ESDA, is a set of spatial statistical protocols designed to detect variances specific spatial data(Anselin, Sridharan and Gholston 2007, Haining, Wise and Jingsheng 1998). ESDA is particularly useful in the detection of spatial autocorrelation – the systematic distribution of data values across space – as well as issues of data clustering and outliers. First, and much like descriptive statistics in stochastic methods, simple mapping of rates and their location tells the researcher much about that data. The following two figures (see , and) plot the location and frequency of Social Disorder Calls for service in Baltimore City as surface trends. The first figure (Figure 2) plots the (x, y) locations and includes a z access of "call counts" it illustrates the spatial diffusion of calls. The second figure (Figure 3) "stacks" calls to their entire, summed count, permitting a quick visual of *where concentrations* of calls are happening in the city. It reveals disproportionate call counts in the Patterson Park and Canton areas, as well as the downtown area. Using another technique revealed whether these distributions were problematic.

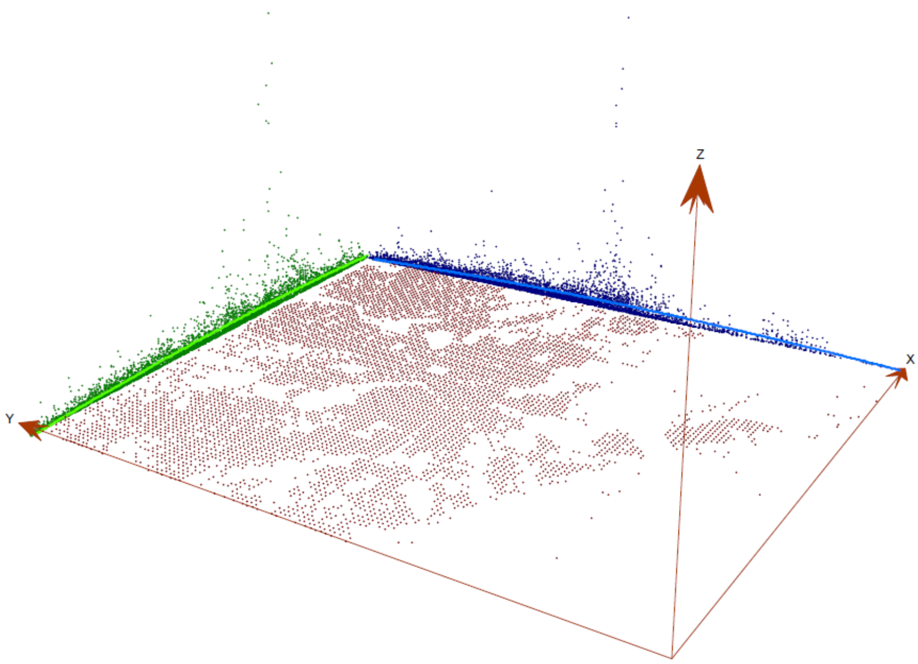

Figure 2 – ESDA - Surface Trend Analyses – Plotted locations of 311 Calls for Social Disorder
The figure shows the spatial distribution of calls made for remediation of social disorder issues across the city, indicating almost the entire city uses the system to some degree. The "green" line locates the northern boundary of Baltimore City.

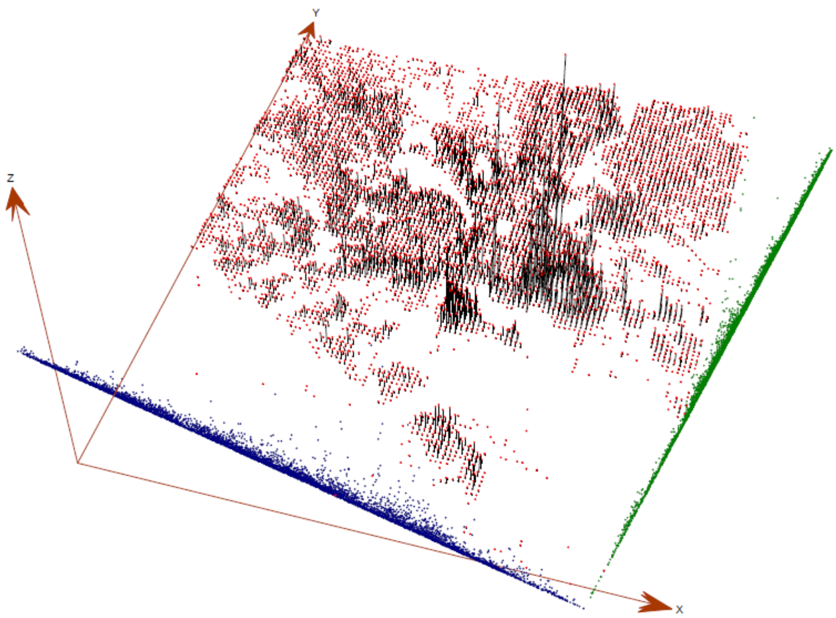

Figure 3 – ESDA – Surface Trend Analysis – Plotted counts of 311 Calls for Social Disorder
This figure demonstrates counts of calls across the city illustrating heavy concentrations of call counts happening in the Patterson Park, Canton and Inner Harbor/Downtown areas of Baltimore. The "green" line here indicates the eastern boundary of Baltimore City.

Next I used ESDA and plotted Normal QQ probability values (see Figure 4) for Social Disorder calls to visually reveal outlier-calling rates on a map. Noting *where* problems are is important because we don't want to remove cases from a data set based on their problematic values. Doing so can eliminate cases we *do* want to keep if that is our local area of analysis (Waller and Gotway 2004). The QQ Plot map showed unusually high rates of calls made in the Patterson Park area of western Baltimore, near Johns Hopkins University in Charles Village (to the north) and areas of Harbor East. Additionally smaller outlier probability cluster values are found in Federal Hill – one

of our research sites of interest. Though relatively minor as outliers of rates (compare Federal Hill's "dots" to those in about Patterson Park) there is markedly less clustering as well of those calls in Federal Hill. That said these outliers in Federal Hill don't need to be removed or transformed. However, one must keep this pattern in mind when interpreting results later. Additionally the Sandtown-Winchester area, to the north of Federal Hill, displays no such probability distribution issues as other areas demonstrate.

I also used Confirmatory Data Analysis (CDA) (Anselin, Sridharan and Gholston 2007) on the calls for service data to ensure that spatial autocorrelation is not occurring amongst observations. CDA attempts to uncover the *structural relationships* among the geographic distributions of the selected attributes. Its strength lies in the implementation of basic econometric analyses while implementing tests for spatial interdependencies between observations; it tests for *functional*

inter-dependence of cases where observations affect other cases near them, mediating and/or moderating those values. For example, litter attracts rats, which in turn very

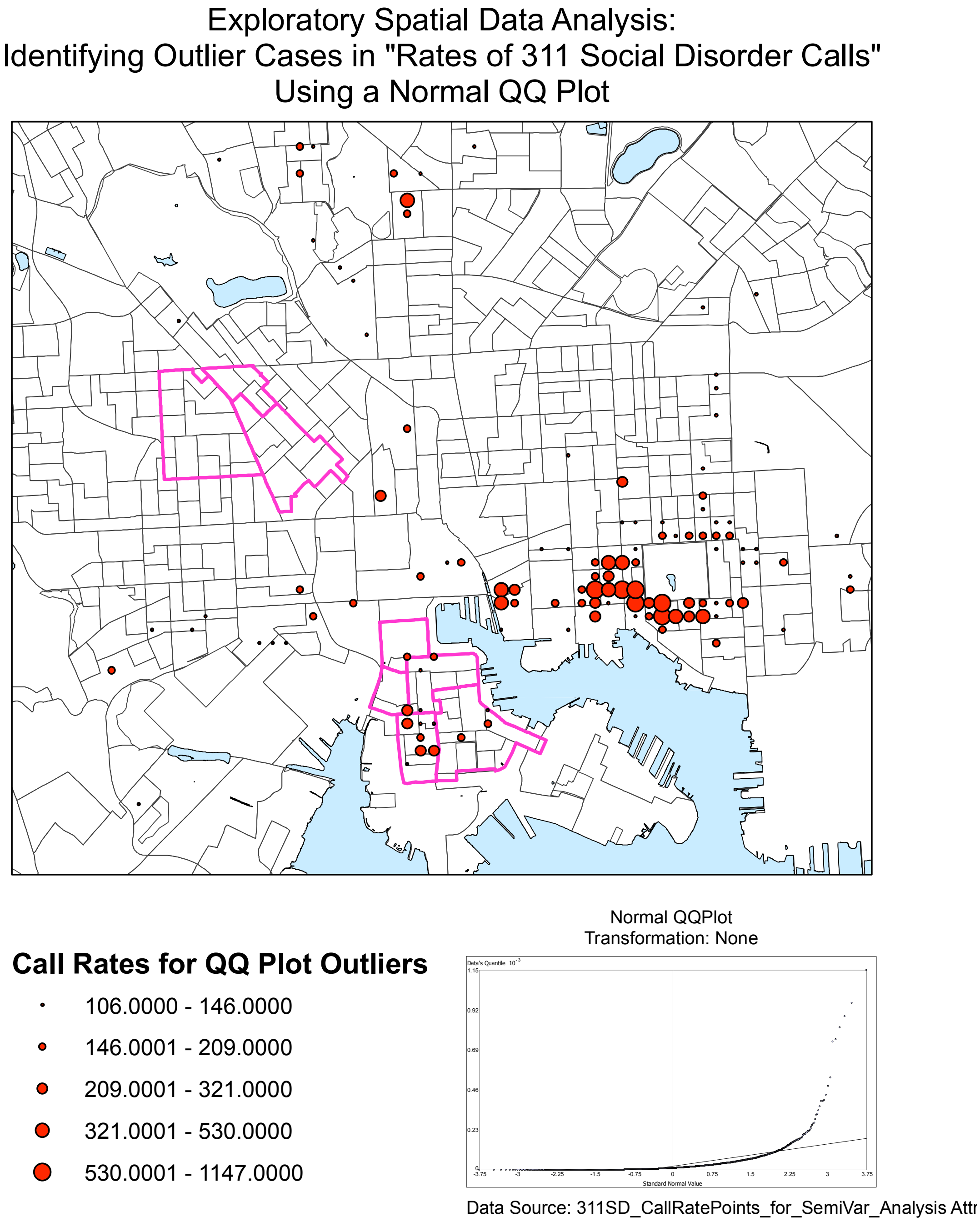

Figure 4 – ESDA and Normal QQ Plot

ESDA can use QQ Plots and map results to identify outlier cases and data.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

likely drives calls about rats. Ignoring possible autocorrelation in spatial data can lead to incorrect inference in relationships of spatial variables, something that is especially evident in aggregated data from the Census where data unit sizes (tracts, blocks, MSAs, etc.) can sometimes submerge the reality of the variation of measures *within* those units (Can 1998). Measurement errors then "spill over" into neighboring units causing what Anselin calls "systematic spatial variation" (Anselin 1998) revealed only through spatial data review methods like CDA.

Using CDA tested data distributions for neighbor variable influences and interaction using *GeoDa*, a simple GIS analysis and visualization tool developed by Luc Anselin (2004) . *GeoDa* is helpful revealing structural, spatial relationships and dependencies of data depending on those relations. For example, adjacency (observations in a bounded area located beside another bounded area and its observations) can affect those adjacent data values. Also exposed are contiguity issues. Every observation exists in a bounded space, bounded by at least one or more neighboring spaces - spaces that might affect that space's values. A housing complex in polygon that shares a boundary with an adjacent polygon in which there is a "brown field" – an environmental health risk site – would likely display effects on measures of health outcomes done in the housing complex area. However, a polygonal space associated, or located contiguously with different numbers of other polygonal spaces *also* affect case values depending on the quality of those spaces proximal (or not) and acting as connectors, conduits if you will .

Residential flight from a city zone to a nearby suburban space demonstrates this effect. Weighted matrices then are derived depending on k-nearest neighbors (how "far out" from the local observation space does one want to test for influence) and lower and higher contiguity orders where lower are those spaces immediately adjacent, and higher ones further out.

Determining Local Patterns of Spatial Autocorrelation – Moran's I and LISA Measures

In order to determine patterned spatial relations of observed measures (within one variable itself) we use Moran's *I* and LISA (local indicators of spatial autocorrelation) outputs. LISA measures are used to detect patterns of spatial autocorrelation (Anselin 1998, Arlinghaus and Griffith 1996, Ord and Getis 1995) where spatial autocorrelation is noted as the phenomenon where *locational* similarity (proximity to other cases of the same variable of interest) is matched with case *value* similarities (Anselin, Sridharan and Gholston 2007). Mapping these values is especially useful in exploratory data analysis (ESDA) (Goodchild and Janelle 2004) and can be used to generate hypotheses on data relationships in space. Moran's *I* then is a statistical calculation, similar to Pearson's cross-product correlation, that works to confirm or refute the hypothesis that a variable's observed case values are randomized in their spatial distribution, across a domain of interest. Two means are calculated for use in the statistic used to determine spatial autocorrelation. First, a global mean is determined from all observations, and then a second a local mean is determined, using a particular distance band, extending from each variable's (x, y) central location in space outwards, and averaging out the included, neighboring, observations of that variable's sister values. The particular, delimited, neighborhood of influence is chosen based on a theoretically sound expectation of spatial influence – how that variable is expected to influence other neighboring variable values, and vice versa. The patterns then of local influence and association of variable influence come in four pattern types as degrees of spatial autocorrelation determined from the Moran's *I* statistic. When a variable's observed value is measured as higher than the means of a delimited neighborhood of nearby observations, then we are witnessing an HL (or high-low) variable value association (See). On the other hand, when variables display measures lower than their local, or neighborhood, observed mean values, they are classified as having an LH (or low-high) pattern of association. The other two patterns result when we compare a variable's locally observed value to that variable's globally measured mean. Similarly valued variables tend to cluster near one another, for example concentrations of observations of wealth in a particular area, and we can identify this clustering when local means (i.e. income) measure higher than the globally measured mean for that variable. These patterns are identified as HH (or high-high) associated observations. Finally when local variable's means are found to be lower than that variables global mean it is said to be a LL (or low-low) pattern of spatial clustering.

Looking at the following mapped values (see Figure 5) the "blue and red" celled maps (Note: the complete set of LISA maps are found in the appendices, page 258). LISA measures tell us is how the variability in spatial autocorrelation *from variable to variable* can be immense. First the maps indicate if the LISA value is statistically significant by plotting the values as *z*-scores. Then the significant values are color-coded for easier visual interpretation with red indicating HH, blue indicating LL, light red indicating HL, and light blue indicating LH clustering is occurring.

Table 2 – LISA (Local Indicators of Spatial Autocorrelation) Patterns of Local Variable Value s

		…the LOCAL Mean (mean of NEIGHBOR values)	**…the GLOBAL Mean** (mean of ALL values)
When an observation is reported as …	**HIGHER than…**	…its corresponding grid square is colored light pink for 'HL' indicating… **HIGH observed values surrounded by other LOW values**	…its corresponding grid square is colored dark red for 'HH' indicating… **HIGH observed values surrounded by other HIGH values**
	LOWER than…	…its corresponding grid square is colored light blue for 'LH' indicating… **LOW observed values surrounded by other HIGH values**	…its corresponding grid square is colored dark blue for 'HH' indicating … **LOW observed values surrounded by other LOW values**

Darker colors (blue or red) indicate similar clustering about similar while the lighter colors (blue or red) indicate *spatial outliers* – diverging case values are surrounded by other, dissimilar ones, and *not* random apparently. While ideally we would not want to see any localized patterns in our data spatial autocorrelation occurs in almost every variable and we have to expect and understand its influence as values vary as "low values surrounded by more low values" etc. Determining directions of clustering helps shape decisions about variable transformation that curtail autocorrelation problems and, more importantly, help when trying to understand the modeling of interactions going on in these localities between variables and as overall models themselves.

I reviewed each of the model's variables, both dependent and independent, to determine possible issues with spatial autocorrelation. I do not report on the independent variable outputs here but instead do so in the results section. What does follow here is an example taken of mapped calls from the subset that comprises social disorder. It aptly demonstrates how spatial distribution of call concentration about something like "housing blight" (see Figure 5) shows variation of clustering even within a very small, geographic space, and how, between the two different research sites, clustering happens in one, but not in the other. High call rates are found surrounded by still other high call rates (HH measures) in the western, southern and central core of the Federal Hill neighborhood. At the very center, however, call rates for "housing blight" are recorded that are lower than the mean of the local neighbors (LH measures).

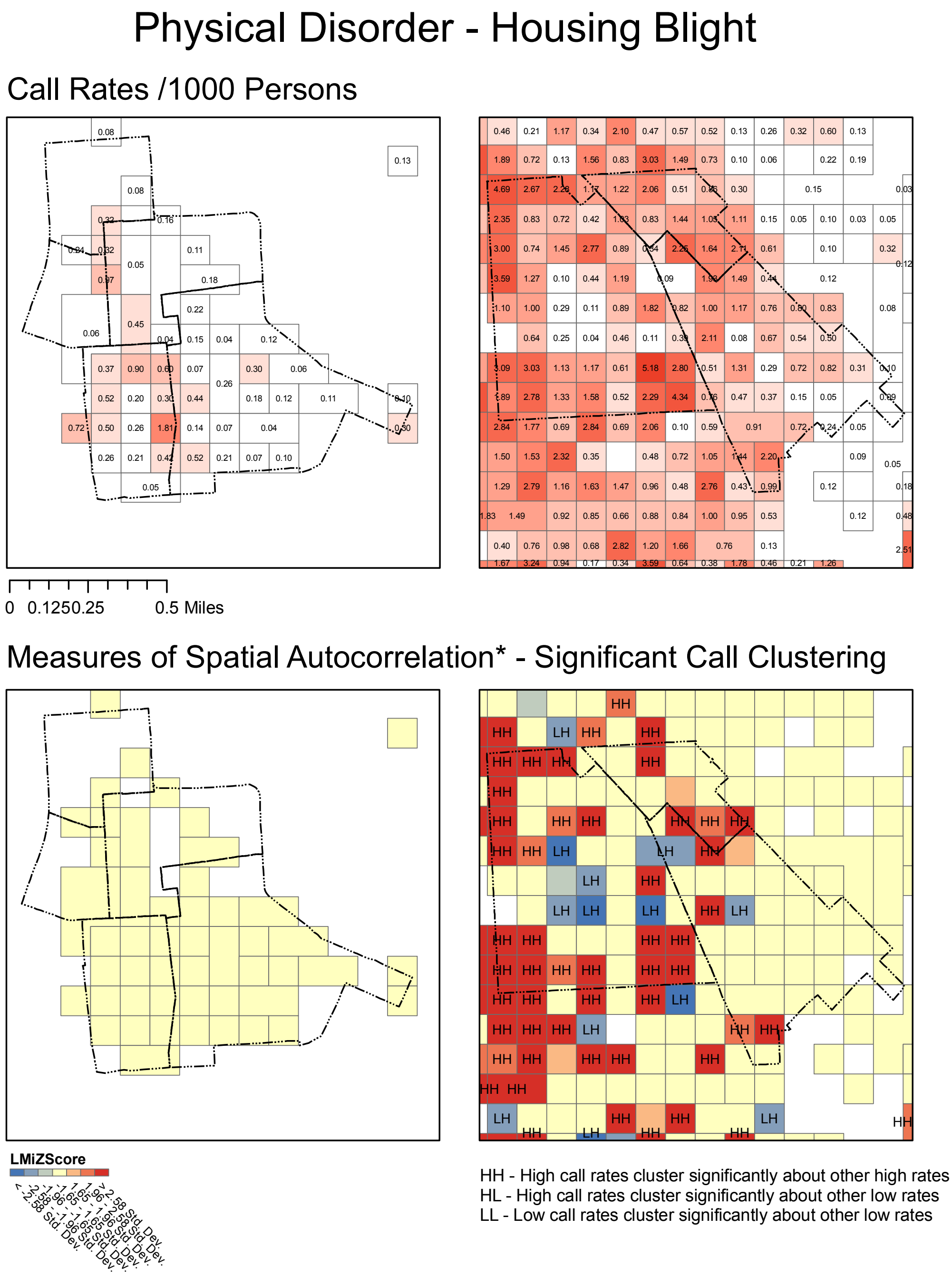

Figure 5 – Example of LISA measures applied to measures of "Housing Blight"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

Again, I refer the reader to all the Calls for Service Maps - LISA Tests – found on page 258, for further review of spatial autocorrelation analyses. Further discussion of the dependent variables and their spatial distribution patterns is found in the results section.

Finally, I tested to determine if the observed patterns of clusters could be measured as statistically significantly clustered data observations. In their recent article *Using Geographically Weighted Regression to Explore Local Crime Patterns* Cahill and Mulligan (2007) discuss how mapped *t*-statistics, derived from the Moron's *I* calculations and LISA values mentioned above, are used to indicate spatial areas in Portland (Oregon) with *statistically significant* clustering of areas prone to crime in Portland. They observe how LISA "(c)lusters … are located in the center of town…" (Ibid , p185) but also note that while it may *appear* there are meaningful clusters of values, without a statistical test we are only "guessing" when looking at mapped images of those. Remember the LISA clusters measure *similarly diverging* values (local values that consistently measure as higher than the local mean, lower than the local mean, higher than a global mean or lower than that global mean) but not the *degree* to which they are measures found beyond statistical chance. To test the degree of statistical significance cluster patterns were evaluated using ESDA analysis before moving on to setting the final model's parameters (see semivariograms below) and running the final GWR models.

Using Luc Anselin's *GeoDa* software (Anselin, Syabri and Kho 2004) I performed analyses on the spatially addressed *t*-statistics first on the final dependent and independent variables in use in the models testing, for example, did clusters of reported call rates that were high cluster about other reportedly high call rates and did these clusters appear because of more than "chance" alone? Ultimately the goal of this analytic step was to test for the spatial *dependency* of any event/observation values on their relation to other, local observed values for that same event. This is a further refinement of the spatial analyses protocols to date since typical, aspatial or stochastic, analyses stop at the significance of the predictor variable without accounting for the influence of those variables on their, local, sister, values. This research protocol then checks how differences in *qualities of space* (social demographic as well as physical, built environment) might have altered calling patterns. Further it tests if those calling patterns are consistently distributed across space – are they statistically randomly distributed as expected – or are they clustered in particular parts of a neighborhood site and doing so beyond a statistical measure of chance alone. This final analysis step illuminated more about the relationship between agency and environment while refining understandings of what local parameters shape people's action patterns in those particular environments.

Semivariogram Analyses – Testing the Spatial Structure and Influence of Model Variables -

To determine if the spatial data of the model (the addressed and mapped variables) are structured in any patterned way I used semivariogram analyses of the data. These tests determine if, for example, individual case values exhibit a trend to decreasing values as the density of that variable's clusters also decrease. On the other hand, perhaps there is a clear trending of the data to lie along a particular directional axis, like southwest to northeast. Unlike Pearson correlations variograms test the *reverse* and instead measure how correlations between closer pairs of observed events and those of more distant a pairs are *less* alike than they statistically are expected to be. As such the semi-variogram is measuring for *difference* (non-correlation) to determine where local spatial influence, including its combined case's influence and power as an *extent*, "drops off". The semivariogram also has a *range* measured as the distance from the left side of the plot to the semivariogram's *sill* (about three quarters along the lag), where the sill is the distance along the lag where non-variance in observations trails off – differences in paired values becomes more random. The assumption of semivariogram modeling is that as observations move further and further apart in space their influence on one another is decreased and so the difference in their two values will be more and more random(Getis 2009) and points separated by a distance greater than the range then are not considered spatially correlated, hence we use a bandwidth to investigate what that range could be. To compute the semivariogram the "nearest average neighbor distance" is the input into the geostatistical analysis framework computed as

$$\text{Semivariogram}(\text{distance } h) = 0.5 * \text{average} [(\text{value at location } i - \text{value at location } j)^2]$$

where *i* represents the location of the first observation and *j* represents the second location. Pairs are compared through all pairs of locations separated by the distance set as h (ESRI 2008). Importantly, the distance chosen for the bandwidth should be based on some kind of *a priori*, theoretically based, assumptions. I chose 500' as a starting point (ESRI 2008), the assumption being residents cared most about their own, local space most, about two blocks out in distance then, from any mapped call rate since I felt calls were most likely made about events within that that space while other problems would remain largely "out of sight, out of mind", if you will.

Distance parameters in the semivariogram then are computed as “bins” and “lags” to help plot measures of difference where the assumption remains, theoretically, that values separated by a distance of zero should be *identical* (the null hypothesis that the difference should be none) and that distance (proximity) to other case values, of the same variable, have no effect on that case’s reported value. “Bins” set the buffer distance around *each case* determining which observations should be paired with it and which should be ignored while the “lag” is the maximum expected distance of influence of all local case variable values on others. The lag then includes the point where case-observed values cease to have impact on one another, the “sill”. Bins are then subsets of the lag, where the lag is divided up into those bins. For example, along a 2500’ lag distance we might have five bins, one at 500’, the next at 1000’, the next at 1500’ and so on. Choosing a lag size effects the outputs of the semivariogram; if the lag size is too large, one cannot detect short-range autocorrelation as it becomes masked. On the other hand if the lag size is too small, there can empty bins where sample sizes within those bins are too small to get representative averages for bins. Within each bin cases are compared and the differences are plotted showing the differences is values between pairs in that bin. We can then compare that bin’s plotted values to the next and so on and see if there is a pattern in non-correlation. The plotted cases, so displayed visually, show differences in values of pairs of cases as we move along the lag distance, from paired values measuring far apart to those closer together as we approach the sill. The final step in semivariogram analysis is to adjust these parameters to minimize divergence of a line plotted through those points – finding a best fitting modeling of where the influence of a variable’s case values stop, and their influence tapers off. Accordingly, the chief parameter adjusted is the lag, or “bandwidth”, to explore and find at what distance a variable’s spatial effects to cease to be of influence on other values (ESRI 2008). This same computed spatial extent of influence is ultimately what is used in the GWR to determine its modeling weights as it computes its calculations.

While a 500' lag theoretically seemed a good starting point it proved too short in modeling iterations to detect the end distance point where spatial autocorrelation leveled off. Adjusting the lag size, through multiple tests, revealed that the best fitting semivariogram range for 311 Calls for Physical Disorder proved to be 2916' (Figure 6) for 311 Calls for Social Disorder it was set as 2963' (see Figure 7), while for 911 Calls for Emergency Social Disorder the distance of influence of cases on one another was measured and set at 2900'. As noted above these bandwidths are the same distances entered into the geographic weighted regression model as the bandwidths used in each dictating the breadth of the moving window, as it moved from case to case, calculating using the so captured values within that bandwidth neighborhood, across the entire spatial plane, as it computed the regression coefficients.

Final OLS and GWR Model Variables, Tests for Normality

This research seeks to demonstrate the utility of employing a spatial modeling approach to understanding and interpreting the problem of neighborhood social disorder and how the qualities of persons living in those spaces affect that space and in turn may be affected by it. Traditional neighborhood analyses use linear, OLS, models and aggregate data, e.g. census tract, or block level, to generate predictive parameter estimates. The ordinary least squares model is the necessary starting point for any spatial analysis as well. An initial OLS model was used to verify the normality

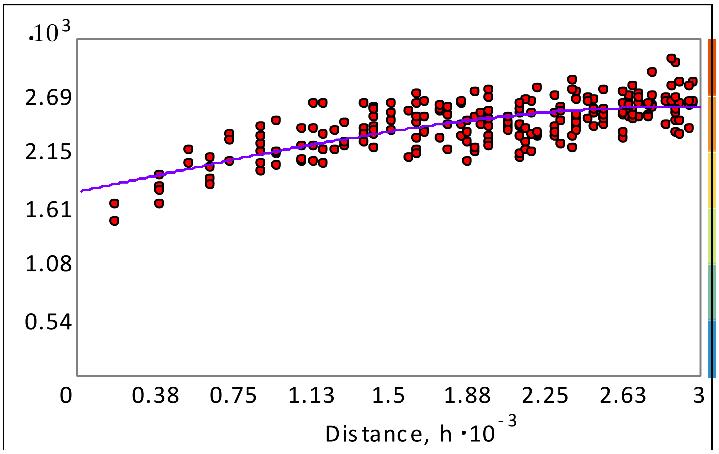

Figure 6 - Semivariogram - 311 Calls for Social Disorder – Range Setting Determination
Semivariogram lag size set to 250’, 12 lags (5000’ total distance) – Range = 2915.93

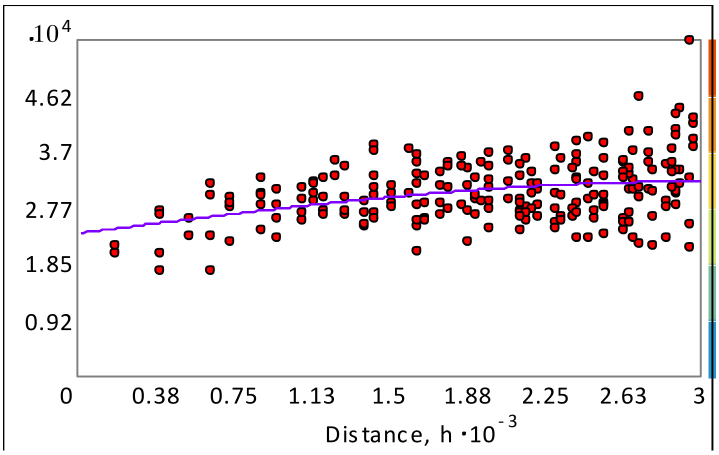

Figure 7 - Semivariogram - 311 Calls for Physical Disorder Rate– Range Setting Determination
Semivariogram lag size set to 250’, 12 lags (5000’ total distance) – Range = 2963.32

of distributions for the final spatial model's parameter estimates, as well as determining if the model proposed was appropriately specified.

The final variables included in the model were chosen based on their theoretically likely contribution to explaining both physical and social disorder in the two neighborhood spaces of interest as well as the theoretically meaningful contribution such variables would make to considerations like social and economic capital within a neighborhood space (i.e. home ownership, presence of cohesive patterns of call rate of residents call *about* something they collectively considered offensive, etc.) According the variables in the following table (Table 3 - OLS & GWR Model Variables) were selected, as derived from the 2000 Federal Census, while others were excluded (see below) along with call rates determined from the Baltimore City's Calls for Service databases. Note that each of the call rate types – 311 Calls for Physical Disorder, 311 Calls for Social Disorder, 911 Calls for Emergency Social Disorder, and 911 Crime Calls - were used as *both* dependent variables in their own respective predictive models *and* as independent inputs in each of the other call type models since, as noted above, use of one level of service may predict knowledge of, and efficacy learned, to use the others.

Testing for Multicollinearity in the OLS Model

Given the social spatial structure of Baltimore means that the city remains starkly segregated racially, economically (including employment distribution, education, home ownership etc.) it is not unexpected that many of the models' variables will display collinearity. However, in order to create a valid model, one that would not favor or distort the explanatory power of any one variable coefficients produced in

OLS & GWR Model Variables

Variable Name	Variable Type	Variable Presumed to be Indicator of Social or Physical Disorder?
Median Household Income	Independent	Social Disorder
Percent Population African American (Race Homogeneity)	Independent	Social Disorder
Percent of Families living in poverty (Families in Poverty/Household Families)	Independent	Social Disorder
Proportion of Local Population with High School vs. Bachelor Degree*	Independent	Social Disorder
Percent of Unemployed Population	Independent	Social Disorder
Percent of Residents who were Foreign-born (Ethnicity Homogeneity)	Independent	Social Disorder
Percent of Residents Moved in the Last 5 years	Independent	Social Disorder
Percent of Houses Vacant	Independent	Physical Disorder
Percent of Homes Owned (vs. Rented)	Independent	Social Disorder
Population Density	Independent	Social Disorder
Rate of 311 Calls for Physical Disorder issues	Dependent & Independent	Physical Disorder
Rate of 311 Calls for Social Disorder issues	Dependent & Independent	Social Disorder
Rate of 911 Calls for Emergency Social Disorder issues**	Dependent & Independent	Social Disorder
Rate of 911 Calls for Crime***	Dependent & Independent	Social Disorder

* For population over aged 25

** Calls where a citizen believes a crime *may be* in progress, i.e. a suspicious person or a threat, versus defined criminal acts)

*** All FBI-defined, Part 2 criminal events and violent crimes, including burglary, theft, assault, rape, homicide, etc. as reported to police

Table 3 - OLS & GWR Model Variables

final model iterations over another, and because all the variables are considered to be meaningfully important to the model, the final model does use the above variables. The intent was to determine what, if any, degree of multicollinearity may create misspecification of the model first, rather than exclude any spatially determined covariance and co-existence of variable parameters that *was* valuable to the spatial modeling of the dependent variable call rates.

The first step in identifying multicollinearity was to run repeated variations of the OLS regression model with the independent variables of interest and look at output diagnostics. Of interest in particular were the variance inflation factors (VIFs) values for each variable. As measure of multicollinearity the variance inflation factor displays eigenvalues for each variable in the model where increases occur as variables in that model exhibit multicollinearity. High VIFs suggest different variables are contributing similar, meaningful, conceptual explanations to that model. Diagnostic observations of VIF values exceeding '10' indicate multicollinearity of variables in that model, and increasing instability in the independence of any associated regression coefficients as VIF values increase (Yan and Su 2009).

Exploratory test OLS models were run with each of the calls for service models, predicting 311 Physical Disorder call rates, 311 Social Disorder rates and 911 Emergency Social Disorder call rates, to determine if any of the parameter estimates chosen were redundant in their contribution to the overall model. Accordingly, while theoretically accepted generally as indicators of social disorder, "female headed households" or "single parented household" were overly collinear with "Percent Black" and were dropped from the model. In addition, the variables "Moved in the

Last Five Years" and "Home Tenureship (in Years)" was found to be redundant and was also removed from the OLS model. Furthermore the Akaike's Information Criterion number, indicating model robustness, was used as an indicator of soundness of model specification and did increase with the exclusion of these variables.

It should be noted that while the inclusion of other call rate types as explanatory variables in their sister call rate types might appear problematic it is valid to include them considering one might be "practiced" in calling about, say, "physical disorder" and then this simple experience and knowledge, about how to use the 311/911 system in one manner, could influence a person's ability and efficacy to use it for *other* issues in need of resolution. Furthermore, spatial statistical analyses recognize that local events affect other actions, across and through the spatial diffusion of those events on and in other spaces. For example, a neighbor might share with one another how they called about a problem and how that problem was resolved (or not) and this might influence other, spatially related, neighbors to follow suit. Neighbors act on their environment while they are, themselves, influenced by environments in which calling happens (or doesn't) as well. Exploratory OLS tests revealed no major issues in VIFs, suggesting the call types were in fact measuring different kinds of calling behaviors. That said, collinearity is expected to some degree, particularly between the three call rate variables (See Results section).

The Geographically Weighted Regression (GWR), Execution and Visual Mapping of Variables of Interest

It is common to apply regression to analyze census and other geographically situated variables to determine the relation between one dependent variable and other predictor, independent, variables. The commonly understood model for such a regression is found in Equation 1, OLS Regression Model, below.

In it, y represents the dependent variable and x_1 and x_2 are the independent variables, while b_0, b_1 and b_2, are the parameters of interest measured, and e represents a random error term. Importantly the measurements of variables are assumed independent of one another and the error term is assumed to be normally distributed. Furthermore, it is assumed that the model we have created is going to be *constant across* space – that the measured values, gathered across that space, have no bearing on themselves, or measures of other nearby variables.

However spatial measures *are not* independent of one another and can demonstrate considerable influence upon one another invalidating, or at least skewing, outcome measures and rendering the a constant model, applied across varying space, as inadequate ((Fotheringham, Brunsdon and Chalrton 1998), (Haining 1990, Haining, Wise and Jingsheng 1998), (Goodchild 1996)etc.). However, geographically weighted regression modeling permits parameter estimates to *vary locally* – parameter estimates spatially closer to one another exert *more* influence in the model while those farther away are *less* influenced (Fotheringham, Brunsdon and Chalrton 1998). To take advantage of this subtle but important difference in the rendering of geography and space on variable values the final analysis step in here employs Geographically Weighted Regression (GWR) to determine how rates of calls for service, resident demographics, and measures of social and physical disorder, are affected by spatial relationships, particularly when predicting call rate patterns.

$$y = b_0 + b_1x_1 + b_2x_2 + e$$

Equation 1 - OLS Regression Model

To do this GWR generates spatial data that reflects spatial variation among the variables (Mennis 2006) of interest while "providing parameter estimates , R^2 values, and *t*-statistics for each data point" as well as *p*-values, which indicate whether those spatial variations and relationships are significant (Cahill and Mulligan 2007, p182). With this added dimensionality GWR models have more success in explaining otherwise unmeasured variance compared to OLS models (Ibid).

Visualizing the methodology of GWR consider viewing the City of Baltimore with its grid of 40,000 squares laid over it. After excluding grid cells identified as unoccupied spaces (parks, water, and industrial zones) what remained were about 30,000 observable cell locations. Each cell and its local values for each variable were computed then as *separates* regression equations while taking into account the surrounding variable values, based on the bandwidths determined by semivariogram modeling earlier. Each regression equation's variable case-values (within a cell location) are weighted using nearby and far-away observations of the same variable. Nearby case values of the same variable are considered to influence other nearby same case values *more* while those further away have a decaying influence, as distance increases, on their impact on a other case values. To compute this GWR uses a "moving window" that steps from cell, to cell, to cell, across the entire city grid, each time looking at a "neighborhood" of case values around that chosen case to measure how that particular value ought to be transformed given local and global spatial variations of other measures of that same variable. Within each of the 30,000 grid squares, the surrounding values of that same variable's neighbors, within a prescribed distance, are used to correct and weight each case value for spatial influences neighboring values exert over that one local observation. The key methodological difference then, with the global OLS model, is that any spatial autocorrelation that we have detected earlier in various tests is corrected and the outputs of the predictive models are expected to be far more robust. The output then, at every grid cell location, is one regression equation, with all its dependent and independent coefficients, R^2 values, error terms and so forth, each calculated acknowledging the influence of more global observations on locally observed case values.

The Calls for Service GWR (Spatial) Predictive Models

Three GWR models were run, one for each of the three different calls for service types: "311 Calls for Physical Disorder", "311 Calls for Social Disorder", and "911 Calls for Emergency Social Disorder". Call rates were regressed on the following independent variables chosen to represent local measures of social and physical disorder and decay, local residents' demographics, and local experiences of crime and violence and the influence of the other, two different kinds of call rate types[10]. As an OLS model it follows as Equation 2. The independent variables included: percent Black population, proportion of those holding bachelors versus high school degrees, percent foreign born, percent moved in last five years, median household income, percent of families living in poverty, percent unemployed, percent of homes owned

[10] While somewhat unusual to include variables so similar to the one being predicted the influence of different kinds of other calling behavior needed to be accounted, and controlled for. Indeed, researchers indicate that the spatial influence and structure of some model variables requires they be both independent and dependent variables within the same research. Goodchild, Michael F. and Donald G. Janelle. 2004. *Spatially Integrated Social Science*. Oxford [England] ; New York: Oxford University Press..

$$\text{Calls for Service} = X_{1\ \text{Race}} + X_{2\ \text{Edu.}} + X_{3\ \text{ForeignBorn}} + X_{4\ \text{Moved Last 5 yrs}} +$$

$$+ X_{5\ \text{Income}} + X_{6\ \text{Poverty}} + X_{7\ \text{Employed}} + X_{8\ \text{\%Vac.Homes}} + X_{9\ \text{\%OwnHome}} + X_{10\ \text{Pop Density}} +$$

$$+ X_{11\ \text{ViolentCrime}} + X_{12\ \text{OtherCalls}} + X_{13\ \text{OtherCalls}}$$

Equation 2 - Predictive Model for Changes in Calls for Service Rates

(versus rented), rate of violent crimes, (defined as FBI, Part 1 crimes) , local population density, and local call rates for the other related, but different, call rate types. All variables were population adjusted and density corrections made using local areal measures.

The weighted least squares model forms the foundation of the GWR, but where it differs is that the latter adds a weighting component to the equation where each variable's value is determined in relation to a point *i* where values closer to point I are weighted more, those further away, less. While beyond the scope of this paper to describe the mathematics behind it, Brundson notes the GWR equation as such (see Fotheringham, Brunsdon and Chalrton 1998) where I draw your attention to *i*, denoting the locations of *n* number of locales the regression is run at – in this case the cells across Baltimore City in the following spatial regression equation:

Using GWR Output – Mapping Coefficients and t – scores

Since the purpose of the GWR is to improve the specificity of modeling social patterns of interest in space mapping the results provides key insights into how measures differ across larger space but also, in this case, within neighborhoods. The local specificity it was hoped would improve prediction measures within these spaces while increasing confidence in the predictive power of our model's constituent variables to forecast calling patterns given those social and physical neighborhood differences. From GIS GWR output then one explores diagnostic outputs and the various model R-square values and parameter estimates for independent variable

$$y_i = \sum_{j=1}^{p} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i,\ \ i = 1, 2, \cdots, n,$$

Equation 3 - Equation for Geographically Weighted Regression (Brundson, 1998 in Fotheringham, Brunsdon and Chalrton 1998)

values, how they are similar or different between neighborhoods of interest, and how, when compared from model to model, are they again sharing the same dimensions of R^2 values, parameter estimates and so forth. This research furthers this technique since most data from GWR has been applied to socio-economic data geographically coded into zones, like census tracts, and not performed with continuous surface data (Mennis 2006) as this project developed for its model inputs.

To visualize differences in the neighborhood sites and their calling patterns I first mapped the R^2 values of both independent and dependent variables, looking for variation in their contributions to calling patterns, noting direction of impact (enhanced calling rate frequency vs. inhibited) as well as degree. Also mapped were the *t*-statistic values. These scores measured the *significance* of each of the models component parameters estimates at each of the cells laid over the city space. So mapped they provided a "continuous surface of parameter values" (Fotheringham et al. in Cahill and Mulligan 2007:181) to determine local and global variation in the significance of different variables on calling patterns within, and compared between, my two neighborhood sites. This spatial smoothing utilization method is important because it generates estimates of *spatially located* influences on the parameters on citizen call behaviors (Cahill and Mulligan 2007) rather than abstract, aggregate measures assumed to affect all residents equally, across all space.

With this exploratory phase of the research completed, I used the R^2 and t-statistic maps and, looking for significant correlations, tried to identify not only statistical patterns but also whether or not discernable spatial patterns or differences existed between the two sites of interest. With major or key differences identified, I finally tried to capture these differences of calling patterns, neighborhood characteristics and social demographic variances as typologies of what constituted these two spaces as different from one another.

RESULTS

In the analysis that follows, I begin with general descriptive statistics of neighborhood and demographic variables. Broadly I look at the types of calls being made, always comparing between the two neighborhood sites, then move to more specific analyses of the three different call type rates of interest – call rates for remedying physical disorder, social disorder and emergency (perceived or immediate criminal) social disorder and the constituent input variables that might predict the rates themselves. Exploratory data analysis visualized the uniformity of concentration and dispersion of both the independent variables and the three call rate types. More specific tests follow showing measurement of the spatial dependence of model input variables, and each of the three call rate types, the dependent variables; this indicates if these components were spatially dependent on one another and allows me to explore whether input variables and call rates cluster in statistically significant ways which could skew regression computations, outputs and hence results and interpretations.

Next, I present the findings from the preliminary tests of OLS model, comparing always the two different neighborhoods for each of the three call types. OLS model outputs also generated model error estimates which were themselves mapped, and tested spatially using Moran's *I and LISA* tests (local tests for indicators of spatial autocorrelation) for indications of model misspecification and, again, that input variables were spatially independent of one another and values random or not. Moving from the global, OLS, model to a local, spatial (geographically weighted regression, or GWR), model, I explored first the differences of each of the three different call rate types' (physical, social and emergency social disorder rates) and their overall R^2 outputs. More specifically then I reviewed the constituent variable coefficients themselves, comparing each of them from model to model, at each of the two different neighborhood sites. The resultant mapped coefficient values illustrated spatial variation in those values and showed spatially, the differences of predictive impact (dependent variable R^2 values) within each neighborhood site. Testing was completed that explored whether or not model misspecification of input variables remained hidden by using Pearson's correlations of local R^2 values between the outputs of the independent variables. Finally, results are presented which plot the geographically weighted regression coefficients for each of the independent variables, at each of the neighborhood sites to illustrate differences in the predictive nature of those values.

Neighborhood and Site Characteristics

Neighborhood Cluster Demographics

Using 2000 Census[11] data I compared the two neighborhood sites of Sandtown-Winchester and Federal Hill on descriptive variables generally accepted as indicators of social and physical disorganization. As stated earlier the two neighborhood sites were purposefully chosen to highlight the differences between those lived-in spaces. Generally, and as expected, the two spaces appear diametrically opposed on almost every measure (see Table 4).

Almost *all* of the Sandtown-Winchester neighborhoods' space population is Black -- 96%. In the Federal Hill group, however Black population never exceeds 25% in any

[11] 2010 Census data was not available at the time of analyses.

of the neighborhoods, and large parts of Federal Hill are almost entirely *white*. Total population from the two neighborhood sites equals 4443 in the Federal Hill set, and 2460 in the Sandtown-Winchester group. Population density isn't particularly different from one community to the next, reflecting similar types of residential buildings and historic settlement patterns.

The Sandtown-Winchester neighborhood is a locale deeply impoverished: more than a fifth of families are living in poverty while families in in poverty measure four times less (only five percent) in Federal Hill. Income measures also show vast differences. Federal Hill residents have a median household income slightly less than $90,000 while most households in Sandtown-Winchester earn below $20,000/year. While unemployment is virtually non-existent in Federal Hill, it runs consistently between 10-15% amongst residents in Sandtown-Winchester.

Differences in income and wealth are reflected in homeownership: only a third of those in Sandtown-Winchester own their own home while two-thirds rent. In Federal Hill about two-thirds of those living there own their own home. Over 40% of homes in Sandtown-Winchester are vacant, even after established community organizations have worked for decades to alleviate this issue[12]. In Federal Hill the "Vacants", as

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[12] It should be noted that Sandtown proper,, the eastern neighborhood in the Sandtown-Winchester neighborhood cluster, has undergone several substantial rehabilitation and rebuilding program since 1990, including Federal Empowerment Zone initiatives and Habitat For Humanity Initiatives. At the time of this writing the 2010 Census data is just being released but vacancy and other numbers were not yet available to compare the impacts of these programs on Census 2000 figures. However, in 1998,

they are called in Baltimore-speak, never rise above 10% and, in most areas, measure below 5% of all housing stock. Education and unemployment figures are also polar between the two sites: Federal Hill residents are almost twice as likely to have completed a high school degree by the age of 25 and they have an unemployment rate four times less than that of the residents living in the Sandtown-Winchester area.

As an indicator of community residential stability, I analyzed the long form Census data question that asked if residents had moved in the last five years. Sandtown-Winchester residents exhibit much less variation overall in their three neighborhoods (with minimums and maximums of 43-47% reporting they had moved in the last five years) compared to the Federal Hill neighborhoods which reported a range of 38-54% of residents having moved in the last five years.

Another measure sometimes considered as an indicator of social disorganization, particularly in urban neighborhoods, is the number of foreign-born persons found there – a more heterogeneous space is said to challenge existing social norms, risking the displacement of older, more conservative norms as different normative cultures mix and clash. However, in the Sandtown-Winchester area, a space arguably more

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the critics were clearly divided on the program's success – Yeoman, Barry. 1998. "Left Behind in Sandtown." in *City Limits*. Baltimore, MD: City Limits. s

Census characteristics of Sandtown and Federal Hill neighborhood clusters

	Mean		Min.		Max.		*SD*	
	Sandtown	Federal Hill	Sandtown	Federal Hill	Sandtown	Federal Hill	Sandtown	Federal Hill
Median household income	$20,318	$36,400	$18,105	$36,400	$21,713	$52,649	$1,934	$6,945
African American population	97.1%	17.3%	97.1%	3.9%	99.3%	35.9%	0.012	0.139
Families living in poverty	20.8%	5.1%	19.0%	2.9%	22.7%	7.8%	0.019	0.019
Didn't complete highschool (+25	12.4%	7.6%	12.0%	3.8%	13.0%	11.4%	0.006	0.030
Unemployed population	18.8%	5.2%	17.2%	5.2%	21.8%	7.6%	0.026	0.017
Foreign-born population	1.1%	1.8%	0.9%	1.8%	1.3%	3.6%	0.002	0.008
Resident-owned houses	29.3%	50.2%	22.9%	31.0%	33.3%	66.3%	0.056	0.145
Resident not moved in 5 years	45.5%	45.4%	43.0%	38.5%	46.8%	54.8%	0.022	0.065

Table 4 – Census Characteristics of The Two Research Sites – The Sandtown-Winchester and Federal Hill Neighborhoods

socially disorganized at first glance, we find the population is virtually homogenous – 99% of the residents are American born and about half (between 47-54%) have lived in the community for more than 5 years. Contrast this to parts of Federal Hill where the percent of "foreign born" residents routinely exceeds one third. One might typify this difference as "cultural diversity" rather than the Chicago School's "invasion" and "immigration" of outsiders, but it demonstrates one problem of social disorganization as a conceptual theory when these two sites display the opposite of social organizational outcomes when compared to their residential makeup and stability demographics. In terms of spatial mobility, large numbers of residents in Sandtown-Winchester, between 30-50% of them, have not lived in the same house for five years or more. The same pattern of mobility is apparent in Federal Hill where between 38-54% reported having moved in the last 5 years. However similar these figures are the reasons for them moving, the residents from each neighborhood space, are highly likely to be different.

Overall, the Sandtown-Winchester neighborhood is composed of a residential space that is impoverished, Black, occupied by a large number of unemployed persons, where most have not ever graduated from high school degree. They are living within a physical space that continues to implode about them. On the other hand, Federal Hill's neighborhoods fare much better when reviewing their social and physical environments and resources. They benefit from a largely educated, mostly white, well-employed and well-off group of homeowners versus renters. Many of these residential descriptive elements are reflected in the kinds of calls made for city services and requests for police assistance in the respective neighborhoods these residents inhabit. I next explore then the kinds of calls made by residents of the city, their frequency and rates. First, I look at the broad categories of social and physical disorder calling patterns across the city, then the neighborhoods themselves and highlight some of the similarities and extremes in call usage between the two different neighborhoods for each of the three call category types. All figures are call rates per one thousand persons.

Resident Calls for Service – Characteristics of Calls About Physical and Social Disorder

City Wide Rate Averages and Comparing Between-Neighborhood Rates for 311 Calls About Physical Disorder.

Physical disorder calls request assistance with everything from housing code violations, graffiti, potholes, and trash and litter to burned out street lights. Figure 8 - Calls About Physical Disorder Issues - Rates per 1000 Residents – below plots these different calls about physical disorder comparing the two neighborhood sites with Sandtown-Winchester marked in blue, Federal Hill in red and the city call rate average, in yellow. I present the citywide rates than follow with a between neighborhoods comparison of their call rates to explore if, just generally the neighborhoods call at the same frequency as most others in the city, and is there is variance in calling patterns between the two neighborhoods for the same issues.

Baltimore, like many cities, tackles the problems of an aging infrastructure of roads and sewage every day and this is readily apparent given the observed call rates for all manner of physical environment problems and offenses. Water complaints, including backed up sewage to broken mains, to open or inoperable hydrants, count as the highest rated service request in the city in the physical disorder category. About 137 out of every 1000 persons, on average, calls requesting help with these issues. Calls for service for street repairs and lighting issues follow next with rates of 75.0 and 48.4 calls per 1000 persons. While water concerns top the list the calls made about physical disorder they have, arguably less environmental impact on residents' quality of life when compared to trash and litter. Moreover, the call rates to address garbage, illegal dumping, and street and alley cleaning are staggering.

By the numbers Baltimore is, and has been for some time, a city plagued with garbage; 1 in every 6 city residents called to have some part of their neighborhood cleaned over the study period with this generating over 40,000 calls each year. Abandoned cars too represent a degree of physical disorder that, by all counts, begins to seem unbelievable: more than *53,000* calls for abandoned cars were made to city services over the three year data period – or 48 calls per *day*.

When reporting concerns that directly affected a residents public health call rates were generally lower. At the lower end of call rates, we find Recreation and Parks complaints (7.3 calls/1000 residents), Graffiti removal (17.9 calls/1000 residents), Dead animal removal (23.0 calls/1000 residents), Forestry and Trees (36.1 calls/1000 residents), and Rat Control requests (46.4 calls/1000 residents). Why the ubiquity of rats does not warrant the same level of calling for "potholes" bears noting. It may reflect a resident's ability to actually get one particular service carried out (a pothole never moves of course, is easier to find etc.) versus another. Alternatively, it may reflect shifting priorities in funding of the civil institution in charge of fixing these problems. It stands to reason too that the experience of different physical disorder issues in one's own backyard drives some of calling behavior patterns as well and we explore the neighborhood differences in call rates next.

Comparing the two neighborhood sites for 311 calls for physical disorder issues one would expect some localized variance. Assuming Federal Hill is "well off" then one might also expect their call rates to be *less* than the citywide rate averages for issues, assuming they face less, on average, physical disorder stressors than others in Baltimore. However, the rates of calling by Federal Hill residents diverge significantly from citywide rates. When reporting dead animals or requesting "rat rub-outs" (rodent control and poisoning measures) Federal Hill residents make calls on par with the city rate but in the twelve other sub-categories of physical disorder call types they call at rates *much* higher than city call averages. Dirty street cleaning calls are three times higher, calls for trash and litter are four times higher and Federal Hill calls about abandoned cars roughly three times higher than the city wide average – 253.2 vs. 83.6 calls per 1000 residents respectively. Now this cluster of neighborhoods does sit adjacent to the stadiums and traffic and parking violations are likely to be constant sources of irritants to the residents and may inflate this rate. Comparing Federal Hill rates on abandoned cars with Sandtown-Winchester we discover the poorer neighborhood has a still higher rate than Federal Hill. The "stadium explanation" alone does not explain why the rate of calls for abandoned cars in Federal Hill is so high and that explanation doesn't work at all in Sandtown-Winchester where parking is easy to come by. All this then points out that the two neighborhoods appear to share *different* conceptualizations of "abandoned car" in their respective neighborhoods, and/or use this tool of informal social control for different *purposes*.

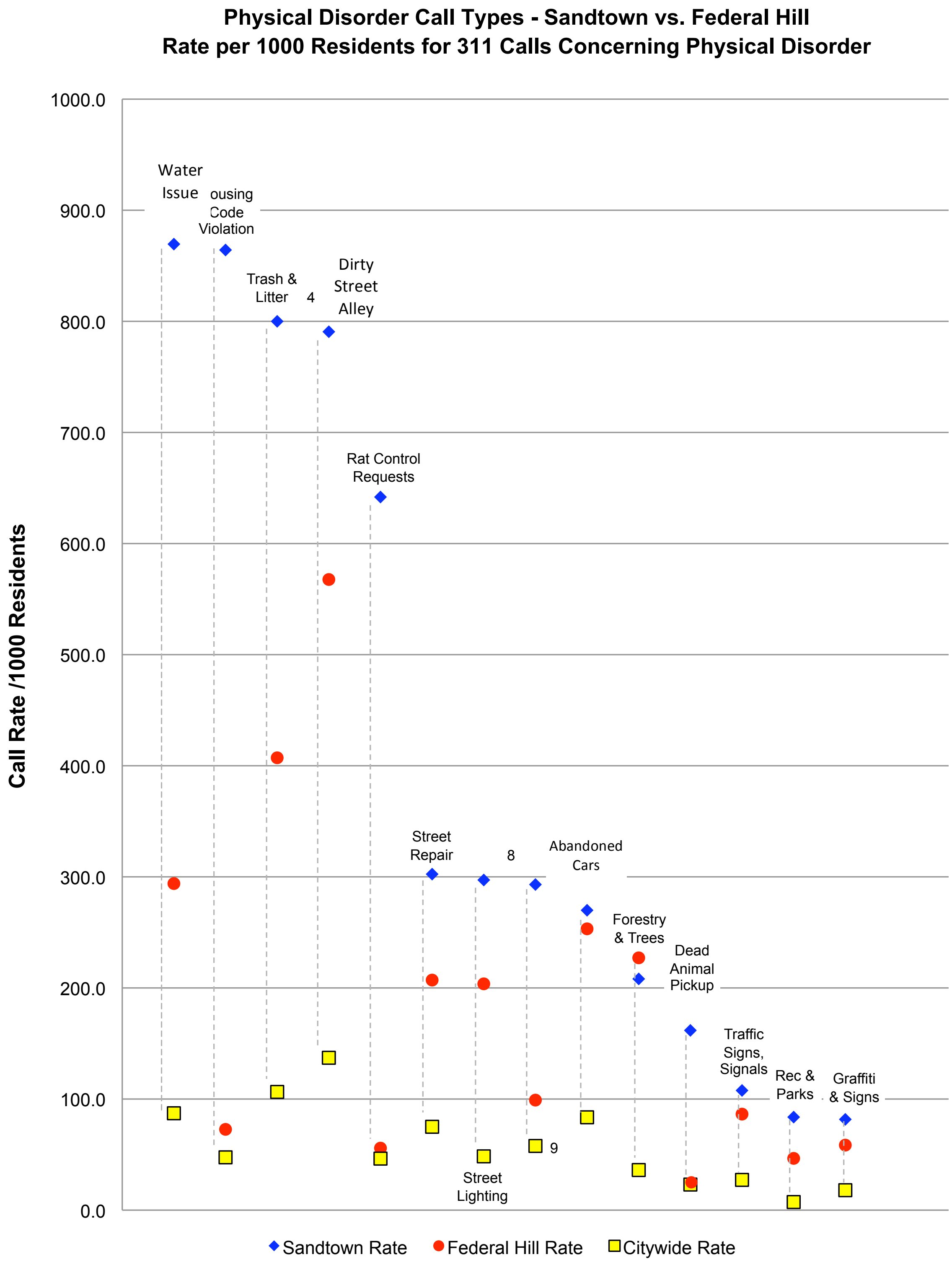

Figure 8 - Calls About Physical Disorder Issues - Rates per 1000 Residents

The rate of calls for issues about physical disorder like trash, high grass and weeds, and rats, in Sandtown-Winchester is generally double what we see in Federal Hill very high compared to the city call averages. Clearly, "learned helplessness" is not a factor in the Sandtown-Winchester neighborhood and residents are trying to effect and rectify these incivilities. Their call rates for trash and street cleaning are two and three times higher than Federal Hill's residents, and almost *nine times* higher than the citywide averages. The same patterns holds for housing code violations where Sandtown-Winchester residents call at a rate of 864.2 calls per 1000 residents, and more than half the residents on average request elimination of rats (641.9 calls per 1000 persons). In fact Sandtown-Winchester people are calling *ten times* as much as their neighbors in Federal Hill to try to rid themselves of trash and vermin. Even potholes don't escape them: they call three times as much as the city average for "street repairs" and, again, almost double the rate of those who live in Federal Hill.

Interestingly, Sandtown-Winchester residents call at rates higher than Federal Hill residents in *every* category of physical disorder, save one: Forestry and Trees services. For this service, the requesting of trees cut down and replaced, grass and green spaces repaired, Federal Hill residents call at a rate of 227.1 calls per 1000 residents. This compared to 208.1 per 1000 persons in the Sandtown-Winchester area. True, these are similar rates. But one need only walk the neighborhoods to see two things: First, much of Sandtown-Winchester is remarkably devoid of greenery to attend to in the first place, and second, there may be a degree of "privilege" to note, and certainly a difference in degree of "problem" when one considers Federal Hill residents devote almost the same amount of energy calling about "tree health maintenance" as Sandtown-Winchester residents give when they are calling at similar rates about

“Animals Running at Large”, “Street repair” and “Dead animal pickups.” Again, all at rates far higher than residents in Federal Hill.

Rates for 311 Non-Emergency, and 911 Emergency, Calls About Social Disorder.

The chart below displays city wide averages for reports of emergencies in need of immediate redress, including narcotics use and dealing, disorderly persons and firearms reported being shot, to more mundane, but none-the-less, immediate and pressing safety issues in a neighborhood like suspicious persons, drunk and intoxicated persons to vagrancy and parking complaints. In each call case type social behavior is the target for corrective informal social controls through calls being made by residents.

City wide call rates are remarkably similar for almost all these types with rates less than 100 calls per 1000 persons, save two types: calls about narcotics/drugs and ones made concerning disorderly persons which are easily ten times higher than other safety issue calls (see Figure 9 - Non-emergency and Emergency Social Disorder Call Types – Rates per 1000 Residents below.)

Amongst call rates for Non-emergency Social Disorder, the most frequently requested issue for remediation in Federal Hill was for parking issues. Compared to the citywide call rate of 92.8 calls per 1000 residents the Federal Hill area’s rate of 948.9 calls per 1000 residents -- more than *ten times* the average rate. The rate for the same issue in Sandtown-Winchester measured 100 calls per 1000 residents, or close to the city average. While one of the lowest calling rates in this category, it was somewhat surprising to find that Housing Violation calls, by both neighborhoods, were very similar in rate measuring 69.9 and 87.3 calls per 1000 residents for the Sandtown-Winchester and Federal Hill sites respectively.

There are other differences to be noted in call rates. Overall Federal Hill is almost precisely aligned with citywide call averages however Sandtown-Winchester's rates are much higher. For example, within the social disorder call pool are calls residents make about "Animal Abuse" and "At Risk Animals" – pets and animals left unfed, unsheltered etc. These calls receive considerably more attention in Sandtown-Winchester at a rate of 339.0 calls per1000 residents compared to Federal Hill, where the call rate was 68.0 calls per 1000 residents, or about five times *less* in Federal Hill than in Sandtown-Winchester. Oddly though *both* neighborhoods call about "suspicious persons" at almost identical rates of calls - Federal Hill residents at 435.7 calls per 1000 residents and, in Sandtown-Winchester, 431.7 calls per 1000 persons. Both rates then are five times *higher* than the citywide average.

Sandtown -Winchester residents called consistently to address this and other abuses and crimes in their neighborhood, and at rates *far above* the city average and Federal Hill residents - almost *ten times* more often than average city residents, including Federal Hill. This is particularly stark when it comes to calling in reports on narcotics or drug dealing and disorderly persons. The highest recorded rate for city callers in the 911 Emergency Social Disorder issues was 524.4 calls per 1000 residents for "disorderly person/s" (see Figure 9), a rate easily five times greater than the next emergency social disorder call issue, followed by the city at an average rate of 460.5 calls per1000 residents for calls about narcotics or drug dealing. Federal Hill shared almost identical rates to the city average. However, in Sandtown-Winchester the rate for disorderly persons calls was *six times* higher than the city and Federal rate average and for drug calls it was an almost unbelievably high rate of calls: 14322.0 calls per 1000 residents - almost *thirty* times higher than the citywide average for such calls. Residents are not to learning to "live with the drug trade" or "giving up the fight" against it clearly.

Overall in emergency social disorder Sandtown-Winchester "bests" Federal Hill in call rates in almost every one of the most *egregious* and dangerous social issues. On the other hand Federal Hill trumps Sandtown-Winchester when calling about the *lowest* level or threshold issues: things like complaints about parking and drunken persons.

Unlike the rates of calls made about Emergency Social Disorder in Federal Hill, the volume of calls made in Sandtown-Winchester paint a picture of a neighborhood under siege. This is clearly evinced by the way in which the Sandtown-Winchester calls consistently in response to "Discharged Firearms", "Child Abuse/Neglect", "Loud Noise Disturbances", or "Juvenile Disturbances" etc. Moreover, given the rate of calls made in response to these events runs easily *ten times* higher than the city *or* Federal Hill rates we can say these residents are vigilant. They are residents in combat, not idly standing by, battling a community in constant crisis.

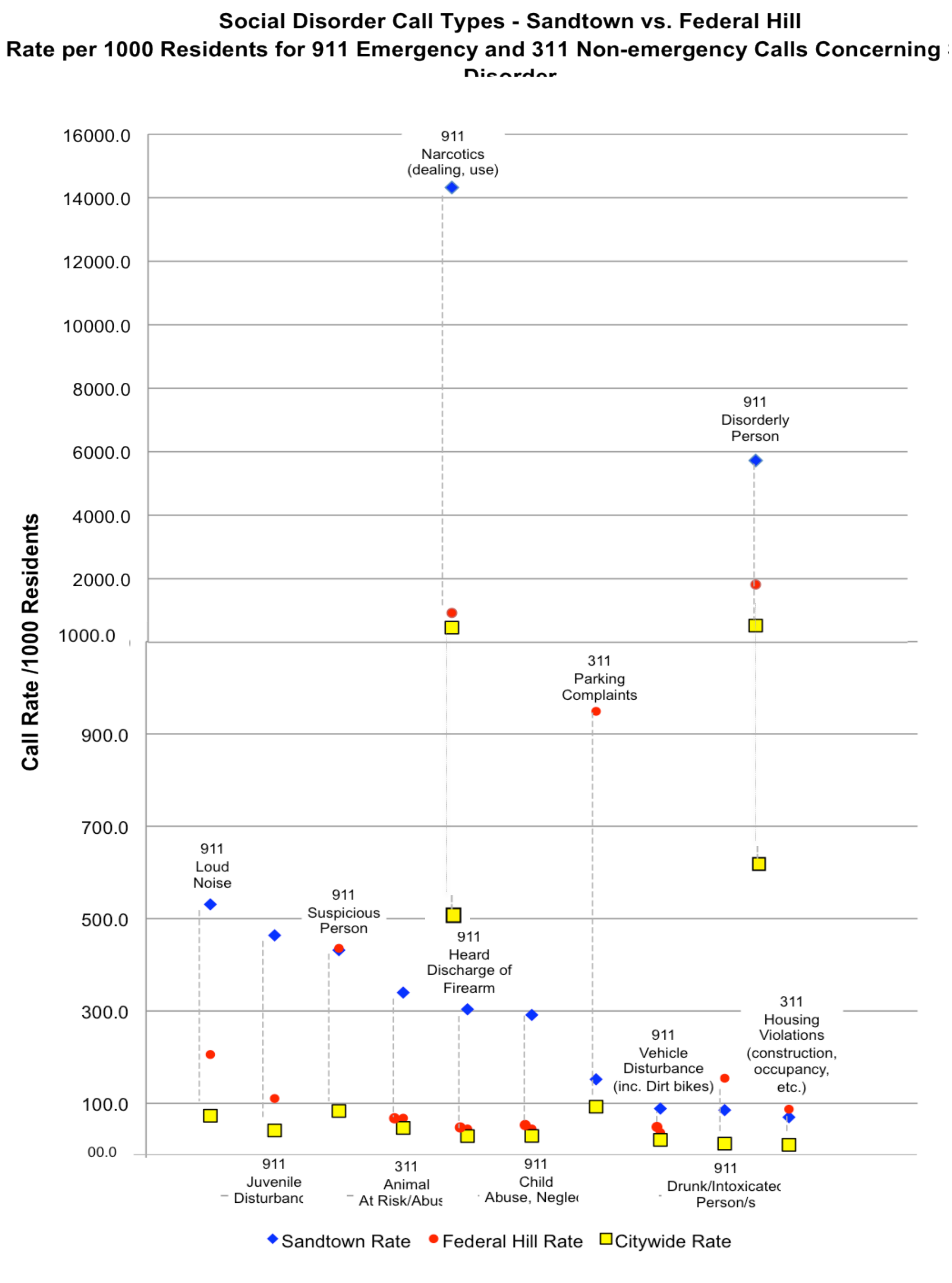

Figure 9 - Non-emergency and Emergency Social Disorder Call Types – Rates per 1000 Residents

I also reviewed call data on violent crimes to see how the neighborhoods varied compared to the city overall, and to one another. Those results follow.

Neighborhood Sites and Citywide Rates for 911 Part 1 Crimes.

The FBI's Part 1 Crimes classification includes crimes violent to a person, personhood or their property[13]. When I used the Part 1 criteria, I found that Federal Hill's crime call rate was 887.9 per 1000 calls compared to a citywide average of 138.8 per 1000 people (). The Sandtown-Winchester neighborhood's call rate was eight times the city average at 2083.3/1000, or a little more than double the rate of calling of residents of the Federal Hill cluster. While it is impossible to causally say whether one place has more crimes, ergo calls more or, alternately, simply feels more compelled to report the "crimes" experienced there, the sheer magnitude of the calls is indicative of the between-neighborhoods difference.

Federal Hill rates for violent crime hovered mostly around the city averages, except for residential burglaries, stolen automobiles and highway robbery (street muggings etc.); these were all about three times the citywide average. Evans, Herbert and Fyfe (1992) note the predilection criminals have for robbing and burgling those with more to steal - richer residents - and so these higher rates there may indicate opportunity crimes.

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[13] Because of the relative rarity of crimes like rape and homicide they were excluded from these measurements. That of course does not diminish the psychic toll that has been extracted on the citizens and residents of Baltimore City who continue to cope with rates of violent crime that put them at the top of the list of the most violent of cities.

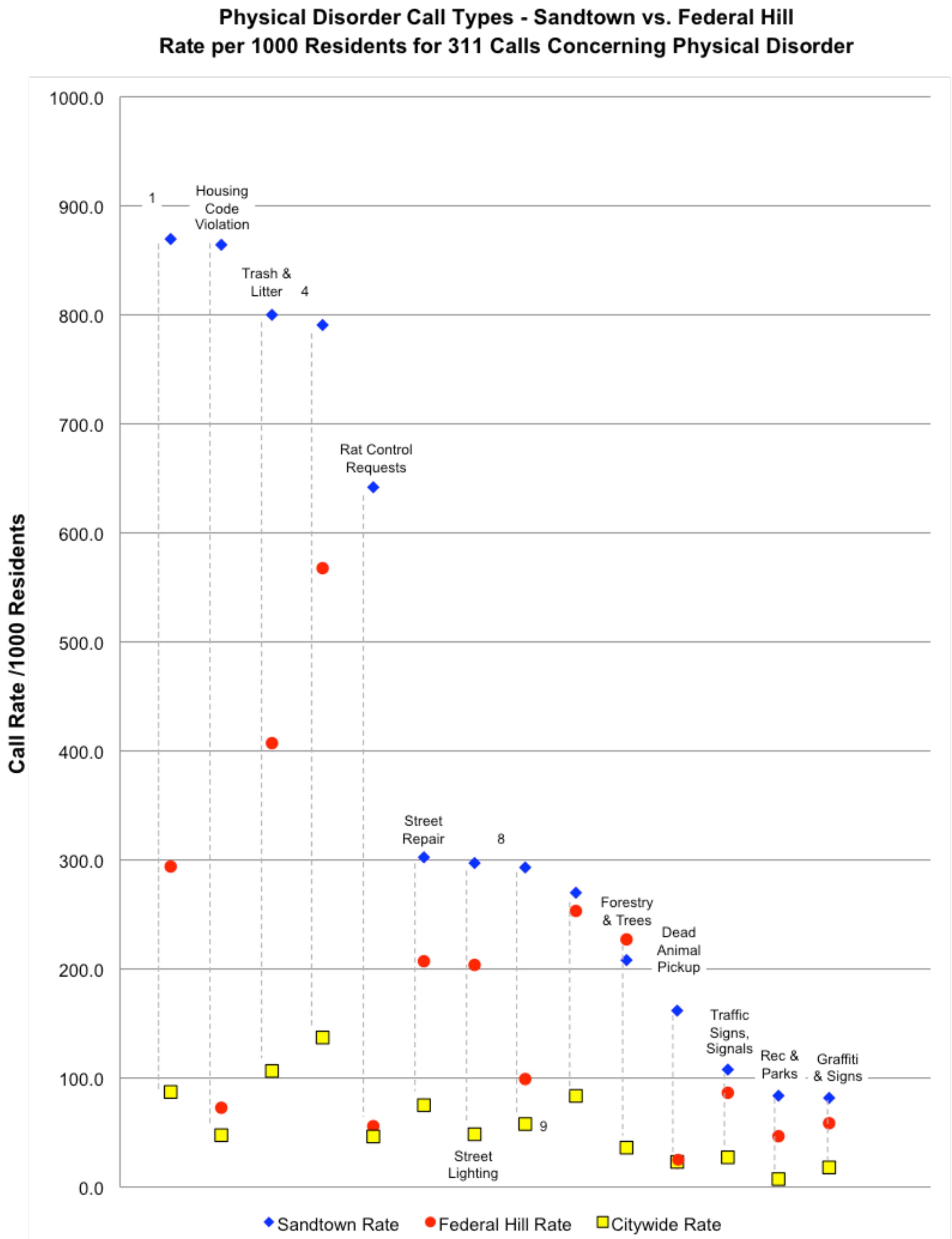

Figure 10 - FBI Part 1 Violent Crime Rates (per/1000 residents)

In Sandtown-Winchester, however, is a far more violent place to live. The aggravated assault call rate there is 520.3 per 1000 residents – a staggering *fourteen times* higher than the city average *and* Federal Hill's rate . The same trend holds true for residential burglaries (six times higher than the city rates and three times higher than Federal Hill), stolen automobiles (seven and three times higher, respectively), highway robbery (*twelve times* the city average, and four times that of Federal Hill), and other forms of burglaries produce call rates nine and three times higher respectively than citywide and Federal Hill rates each make for a tenuous space to call one's home at best.

Spatial Distribution of Dependent and Independent Variables

Spatial Distribution and Variation of 311PD, 311SD and 911SD Call Rates. While the above rates were determined from spatial data they are problematic in that they represent spatial aggregates – summed and averaged values without a particular bounded space, in this case within the boundaries of Baltimore City and the respective neighborhoods of interest's boundaries. Here, I attempt to discern within-neighborhood variation and then between neighborhood differences in internal homogeneity patterns. I do this by focusing on the three different kinds of call types: 311PD, 311SD and 911SD vary within these geographic spaces (See 139). Each map presented uses population-adjusted rates of calls for service, those calls made by local residents, within a 250' x 250' block (cell) of spatial resolution, roughly the size of a city residential block in these neighborhoods. Population at that local resolution was determined from the census tract and used to create a rate so residential density would not distort observed rates.

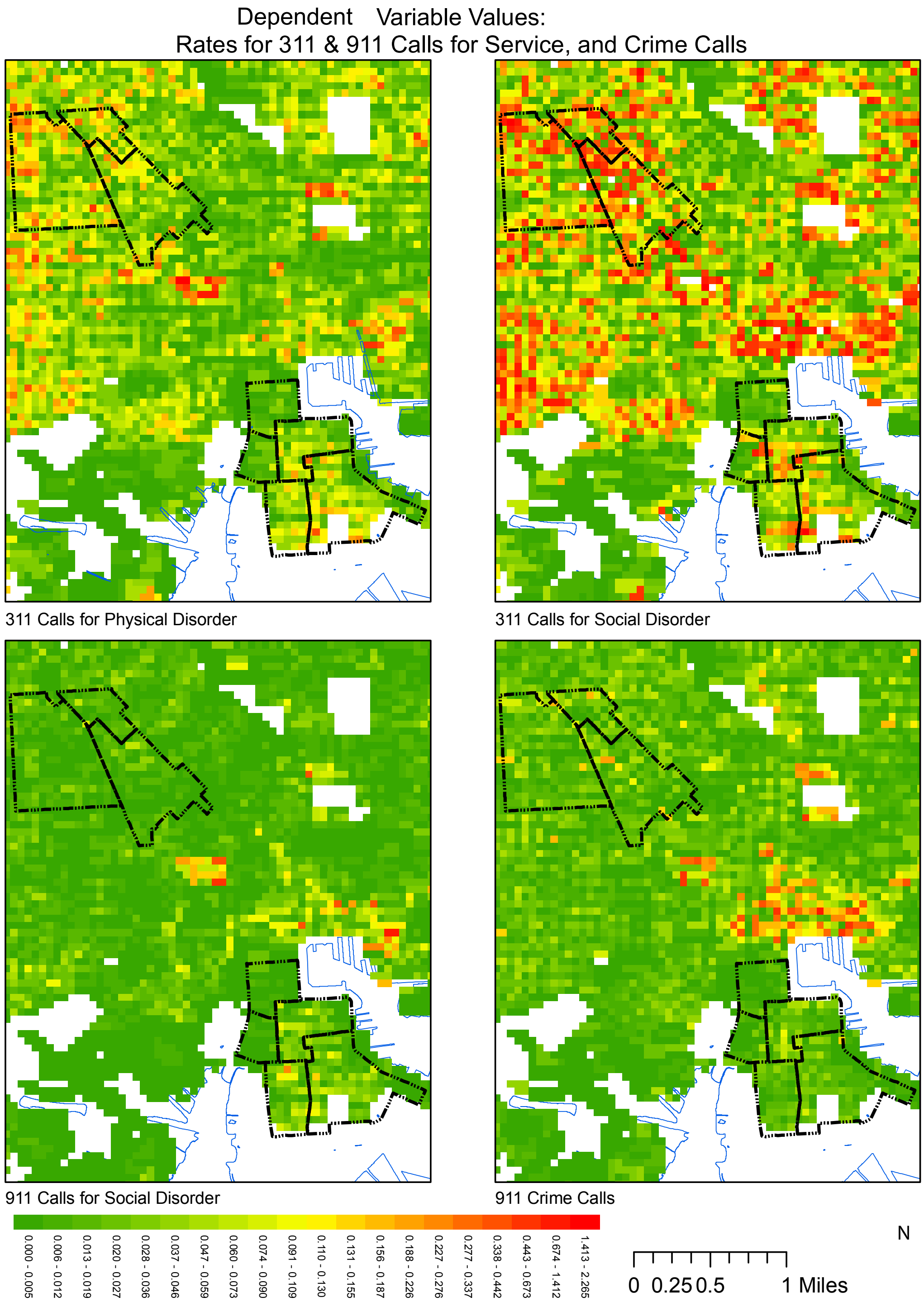

Figure 11 – Dependent Model Variables – Rates of 311 and 911 Calls for Service (Rate calls per/1000)

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

I also include population adjusted 911 rate of Part 1 crime calls in this set of map investigations to see how differences in sheer volume of calls might explain more micro-location calling patterns for the other kinds of calls for services types.

First, generally speaking the patterns observed when comparing the three call type rates (311 physical disorder, 311 social disorder and 911 emergency social disorder), we find significant variation in the rates between each of the different call types (). This appears especially true where there are "commonly traveled spaces" – intersections through which neighborhoods connect to other spaces - where rates appear to be similar. For example, the area located just north of the Inner Harbor exhibits deeper concentrations of <u>all</u> types of calls and shows a marked difference in 911 *crime* calls made. To a much lesser extent there appears to be similar patterning in the north neighborhood of the Federal Hill cluster, Federal Hill proper, the area closest to the Inner Harbor.

Comparing one to the next, the maps illuminate that the usage of 311 and 911 call services varies dramatically within these spaces. In terms of spatial distribution, calls for 911 emergency social disorder (bottom left) as calls not for crime per se, but *perception* or threat of crime, suspicion etc., are almost entirely, uniformly spread across both neighborhood spaces, and in fact over the larger part of midtown and downtown Baltimore as well. Compare this to 311 social disorder call rates (top right) that vary, and swing wildly, depending on the space – and illustrate concentrations of calling in *much* higher rates than actual emergency 911 call emergency call usage. The spatially undulating rates of calls for non-emergency social disorder appear to have little or no correlate in spatial pattern to *other* call type rates. That is to say that while one might posit social disorder breeds "crime" the maps suggest otherwise, and this is information otherwise lost in aggregate statistics. Instead, pronounced high call rate areas are punctuated by nearby lower rate areas right side by side. Call rates for such disorder calls then do appear to have pockets or clustering perhaps, but also may be very local in effect and influence while remaining independent of cause and effect relations with other call types.

The map for physical disorder calls (broken windows, potholes, trash and weeds and so forth) appears in the upper left. While there appears to be a pattern to call rates for physical disorder, following major arterial road lines going north, one sees *lower* rates of physical disorder in the *interior* areas of Sandtown-Winchester neighborhoods, while the *opposite* appears to be the case in the Federal Hill group. Here, in the southern interior, there is substantial variation in the increase in physical disorder calls, at least from a cursory look at the data. In the next section I test whether or not these apparently clustering rates *actually cluster significantly or not*. For the moment, though it is important to point out the *spatial heterogeneity with* a neighborhood, and how mechanisms of even one kind of calling type might be different compared to another. Consider perhaps the difference of interior neighborhood versus exterior identification of social disorder in the two neighborhoods.

Surprising too is the *uniformity* of rates about 311 Calls for Physical Disorder when comparing the two neighborhoods. Except for some trailing off in the northern part of Otterbein the rate of calling is fairly high and consistent. This suggests that *both* neighborhoods value correction of physical disorder (as an aggregate of all values of the constitutive component call rates) to more or less the same degree, and act accordingly to correct those disorders so identified.

Finally, while call rates for 911 emergency social disorder (bottom left) are, largely uniformly spread across the Federal Hill neighbor space, there are noticeably higher rate clusters within this group's neighborhoods - clusters that are completely absent in Sandtown-Winchester. In fact, in aggregate call component types, the Sandtown-Winchester area exhibits some of the lowest rates for combined emergency social disorder issues compared to neighboring downtown environs. The bottom right map, showing rate of 911 Crime calls, shows that while Sandtown-Winchester has shown in rates of crime to be higher than most parts of the city overall there is no particular concentrations of reported crime within the neighborhood space. The uniformity of crime is perhaps even problematic – without clusters to identify where does one start to work to eradicate it. Next I look at the individual model variables, how they vary in space in these neighborhoods followed by tests to determine if their reported values are clustering due to more than just chance.

Spatial Distribution and Variation of Neighborhood Demographics Values

Above I discussed the observations of census data showing how the two, Sandtown-Winchester and Federal Hill, neighborhoods varied on certain demographic measures. Briefly here I present findings showing how those observations differ within the neighborhoods, again emphasizing that spatial variation is obscured when using aggregate data measurement tools. The importance of recognizing this stems from the fact that in global models, ordinary least squares ones, variance and error is corrected in the aggregate.   Here, I look at my variables with greater spatial specificity..

Income is relatively "pocketed" in Sandtown-Winchester – small areas of higher and lower incomes surround and punctuate one another in that space (see appendices, , page 213). In Federal Hill income spatial distribution differences shares a uniform 'arc' along the eastern side of the cluster. Not surprisingly unemployment in Federal Hill matches this same arc. In the top right, unemployment is heavily clustered in the Sandtown-Winchester neighborhoods group, especially to the south, where, following it out of the neighborhood rates increase. This "spatial trend" could indicate a "job desert" – an area of little or no available employment, not surprising for the Poppleton area of Baltimore, perhaps.

The spatial depiction of the foreign born values (see appendices, page **Error! Bookmark not defined.**, bottom left) shows us that much of that population has moved into the east side, along the edge of Federal Hill that now houses the *Ritz Carlton* million dollar homes. To the north the spatial uniformity of distribution of "American born" residents is clear. Looking at neighborhood stability the measures indicate that not all spaces in the Sandtown-Winchester neighborhoods group are as mobile as others – the western neighborhood of Sandtown-Winchester (proper) appears to have <u>no</u> mobility at all while the eastern neighborhood of Upton constitutes the majority of residential movement in the (see appendices, page 213, top right). Given the absence of employment in this space this may not be surprising. While the racial make-up of Sandtown-Winchester's neighborhoods is almost 100% black the Federal Hill cluster reveals the historically black Sharp-Leadenhall neighborhood on its western border as a kind of aberration (see appendices, page 214). The area is, it should be noted, home to the cluster's only large public housing project. More generally, the map depicts the stark racial segregation of neighborhoods that persists even today (what Massey and Douglas called “hyper-segregation” (Massey and Denton 1993).

Moving clockwise (see page 214) both neighborhoods exhibit random distribution of population density, as expected. On the bottom left map, spatial distribution of percent of families living in poverty reveals that embedded problem along the southeast edge of Upton where 61-75% of residents are poor. On the bottom right of the map, we can see how the concentration of university versus high school degrees is striking in the Federal Hill space, yet almost entirely absent in Sandtown-Winchester.

Maps showing the presence or absence of vacant homes in the two neighborhoods illustrate spaces that are particularly vulnerable to decay, loss of tax revenues, etc. (see appendices, page 214). In Sandtown-Winchester group, the Upton neighborhood there has the most social and economic problems and also the most vacant houses and the lowest level of home ownership – less than 5%. On the other hand in Federal Hill, vacant homes are fairly equally distributed across the area and homeownership is high and uniform throughout.

As part of basic regression assumptions before modeling any regression model one must determine whether or not the model’s variables are independent in their co-variation. For spatial data this tested using measures of spatial autocorrelation to determine the influence of one variable’s value on local, other, same variable values. It is those test results I discuss next.

Exploratory Spatial Data Analysis: Spatial Autocorrelation and Clustering

Testing for Spatial Autocorrelation.

Before proceeding with global regression modeling it is imperative to test the model variables, their values as found distributed across the space of the sites of interest, to determine the extent to which variable values are spatially dependent on one another. This spatial non-normality of variable value distributions is known as "spatial autocorrelation" (Anselin 1998 below, Rogerson 2006). Tests measure the influence of variables of the same domain on one another. For example, we are not surprised to see residential spatial patterns of ethnicity in neighborhoods, concentrations like persons living nearby other like persons. The same principle applies to other spatially observed phenomena and that relationship then has to be measured, and corrected for, to determine independent influence of associated variables on these spatially autocorrelated ones. Using distance measures the protocols note the increase or decrease of variable values as proximity to other variable values, from their same domain set, differ from local (within a prescribed distance) and global means of that all that variable's partner values. The measures tell us two things. The first is the pattern of spatial association variables of the same domain share. For example do we variable measurements showing values similarly high and divergent from a measured global mean value? Alternatively, do we find variable difference from mean values routinely high in some observations and routinely low difference from mean values in other, nearby variables? Second, spatial autocorrelation results also show us whether the clustering patterns we observe are due to chance alone. For each of the patterned possibilities we might think we are seeing we can go a step further to the patterns and their import.

LISA Maps: Visualizing Spatial Clusters of Dependent Variables - Call Rates.

Looking at the results shown on the following maps, I tested for significant clustering of the dependent variable outcome in each model: the call rates for 311 Physical Disorder, 311 Social Disorder, and 911 Emergency Social Disorder. This tests for uniform spatial distribution. This helps determine how much, and of what type, if any of the outcomes had spatial autocorrelation present. Ideally data would display random and *dispersed* colors throughout the landscape plane on the maps produced – a few cells grouped together of the red and blue indicator colors. Large patches of blue and red together would indicate the values occurring (the call rates) at those locations were *not* occurring because of random chance. Rather they were likely due to some interaction with another unmeasured variable or even an included variable influencing other local observation values. However, clusters of values do *not* necessarily mean the values are incorrect – rather they highlight that the spatial qualities *in which those values occur* need to be attended to - the model has to be better specified perhaps to determine what *is* influencing these values if it *isn't* chance alone.

Recall that rather than a normal curve testing normality of data LISA maps (Local Indicators of Spatial Autocorrelation maps) test local data points against the *area* mean and compare how that value relates relative to that mean (rather than the *entire* aggregate neighborhood.) It then displays these relationships graphically with maps depicting observations with high mean call rate values clustered about other high rate values graphically as deep red cells (HH), low mean call rate values around other low rates as dark blue cells (LL), and where an observation's data point is *higher than the local mean* it is displayed as pink cells (HL), and when that observation's reported value is lower than the local mean is displayed as light blue cells (LH). White indicates no clustering of values and not all colors appear in all maps unless those spatial patterns are in the data. Remember too that clusters do not imply significance, they are simply observed as such. Moran's I tests are computed next to determine if observed clusters happen for reasons beyond chance alone.

For call rates concerning physical disorder (see Figure 12, top left), clustering of high values does appear within the interior of the Federal Hill neighborhood, particularly along the Light St. corridor and about Riverside Park; but overall, it is relatively low compared to Sandtown-Winchester where, along the peripheral edges of the area, clustering of high values is significant. These high call rate clusters lay over the major thoroughfares that surround this neighborhood,

Rates of calls made about physical disorder show high rates about other high rates clustering in the western portions of Sandtown-Winchester. In Federal there is some minor clustering along Light Street. to the south. Calls for non-emergency social disorder show significant clustering of high rates in much of Federal Hill but almost no clustering of calls, high or low rates, whatsoever in Sandtown-Winchester. This suggests high activity is relatively uniform in Federal Hill but also that Sandtown-Winchester rates are unremarkable compared to area means – neither low nor high rates are observed. For Emergency 911 Social Disorder call rates (bottom left) we see large areas of clustering of high values in Sandtown-Winchester mostly with a little of lower than expected calling behavior along "corridors" (Fulton St., for example) indicated by the light blue squares on the map. were recorded as *lower* than the area mean. There is basically no clustering of rates in Federal Hill. Finally, 911 crime call rate values show little clustering in either neighborhood (bottom right).

The above *LISA* tests highlight spatial autocorrelation issues for the dependent variables in each model: the three different kinds of calls residents might choose to make, and 911 emergency calls (which they are generally compelled to make). In summary the two neighborhoods' calling rates are fairly, uniformly, spatially distributed when considering calls made about physical disorder. However, Federal Hill displays clear concentrations of higher average call rates (many red cells together) when it comes to reporting general social disorder issues in their neighborhood while Sandtown's rates are unremarkable. However the reverse is true for emergency social disorder: here it is Sandtown-Winchester residents who are much more engaged in making calls about emergency social issues and seeing high rates about other high rates while in Federal Hill rates are neither higher or lower than the area mean, nor clustered in any kind of pattern. Finally, call rates in response to 911 violent crime issues appear to be uniform across both neighborhoods.

Next, *LISA* results and maps reported below illustrate how the independent variable measures, those indicators of social and physical disorder used in the predictive models, demonstrate how spatially distributed their values were, illustrating uniformity or variance in results across each neighborhood space, and if there were any pattern differences between the two neighborhoods.

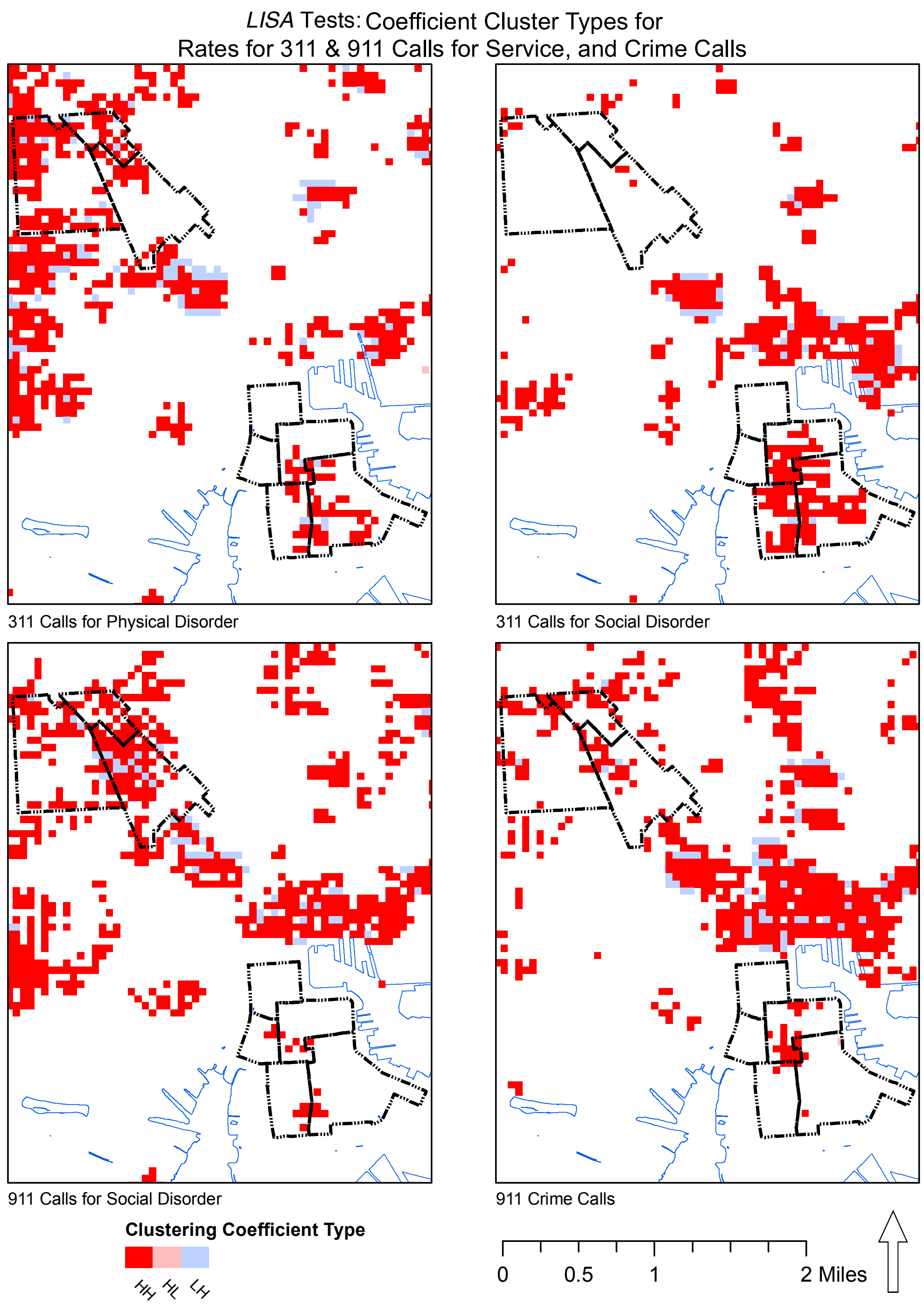

Figure 12 – *LISA* Tests - Coefficient Cluster Types for Dependent Variable Call Rates for all Models

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

LISA Maps: Visualizing Spatial Clusters of Independent Variables - Neighborhoods

To test that aggregates of specific *kinds* of services requests (calls) were not problematically spatially-dependent within, or between, the two neighborhoods, LISA maps were constructed and reviewed for cluster patterns and uniform spatial distributions. For example, the variable used in all models predicting rates for '311 Calls for Physical Disorder' (see Figure 12) includes, in its aggregate rate, calls for service rates based on action requests made for abandoned car/s, street lights, graffiti, trash, high grass and weeds etc. The LISA tests check for spatial dependence of those aggregated rates. For the sake of brevity I include only those maps inline here that indicated differences within or between the neighborhoods' call rates. The remainder of the maps can be found in the appendix.

LISA maps show that "Median Income" measures were, unsurprisingly, uniformly spatially distributed as low values about other low values (dark blue cells) in Sandtown-Winchester and high values about high values (red cells clustered together) in Federal Hill (see Figure 13. top left.) Again, unsurprising is the map showing "Unemployment" as blue cells clustered together in Federal Hill (low measures surrounded by low measures) and high measures of unemployment counts clustered together in Sandtown-Winchester. Percent Foreign Born doesn't show any significant patterns of clustering in Federal Hill though Sandtown-Winchester is uniformly covered by lower than average measures of households with Foreign-Born persons. LISA maps for household residential stability suggest some clustering of lower than average measures along the northeast axis of both neighborhood spaces – high than average residential turnover. The remainder of both neighborhood spaces has neither higher nor lower than average residential instability.

The next mapping of variable measures indicating their spatial uniformity of distribution and values shows Sandtown-Winchester's neighborhood to be incredibly uniform and higher than average in "Percent Black" population while Federal Hill's population is almost entirely white and again uniform (see Figure 14. top left). The LISA map for this measure does also show a collection of pink cells on the western edge of Federal Hill –values of "Percent Black" that are higher than the area mean – hence, surrounded by more white population. This is in the Sharp-Leadenhall public housing area of Federal Hill, which may explain this pocket of higher percentage of black residents. It also emphasizes how segregated race remains, even when "integrated" into a more well off community.

Population density is high in both neighborhoods and surrounded by similarly high densities (see Figure 14, top right). Percent of Families Living in Poverty show higher than locally measured means and heavily clustered in Sandtown-Winchester, while Federal Hill shows two clustered areas – one in central and one to the north, in the Otterbein area, that demonstrate lower than expected measures of poverty compared to the area mean measure. Again, there is one cluster of "red cells" to the west, the same location as the pink cells noted above for Percent Black, but in this case indicating highly clustered poverty in that public housing area. (Figure 14, bottom left). The final map in this series indicates, as expected that Federal Hill shows a much higher and level of education attained (Persons with Bachelors Degrees) than the area average. This is in contrast to the uniformly distributed lower education in Sandtown-Winchester.

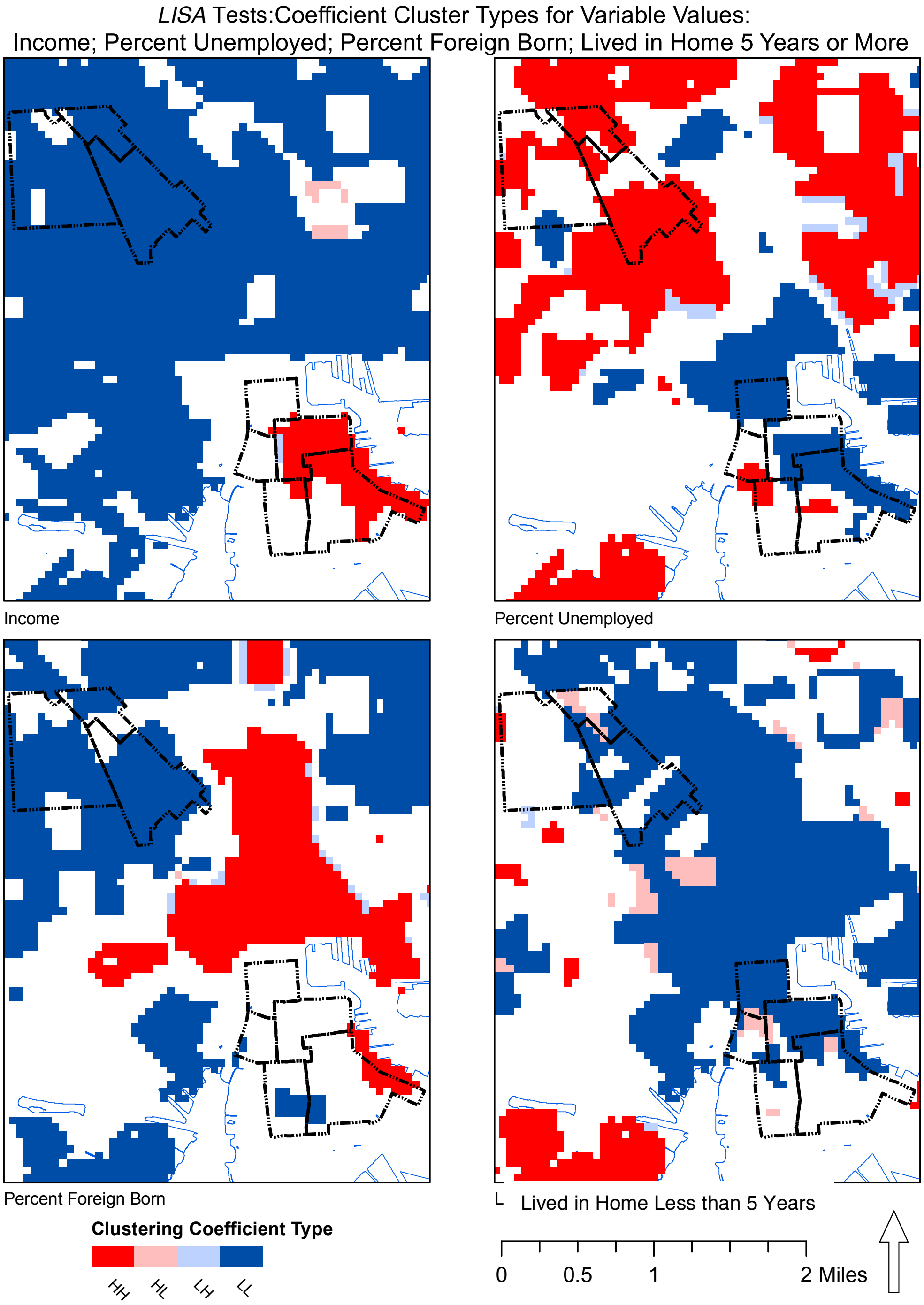

Figure 13 – *LISA* Tests – Coefficient Cluster Types for independent variables Median Income, Percent Unemployed, Percent Foreign Born, and Lived in Home Less than 5 years.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

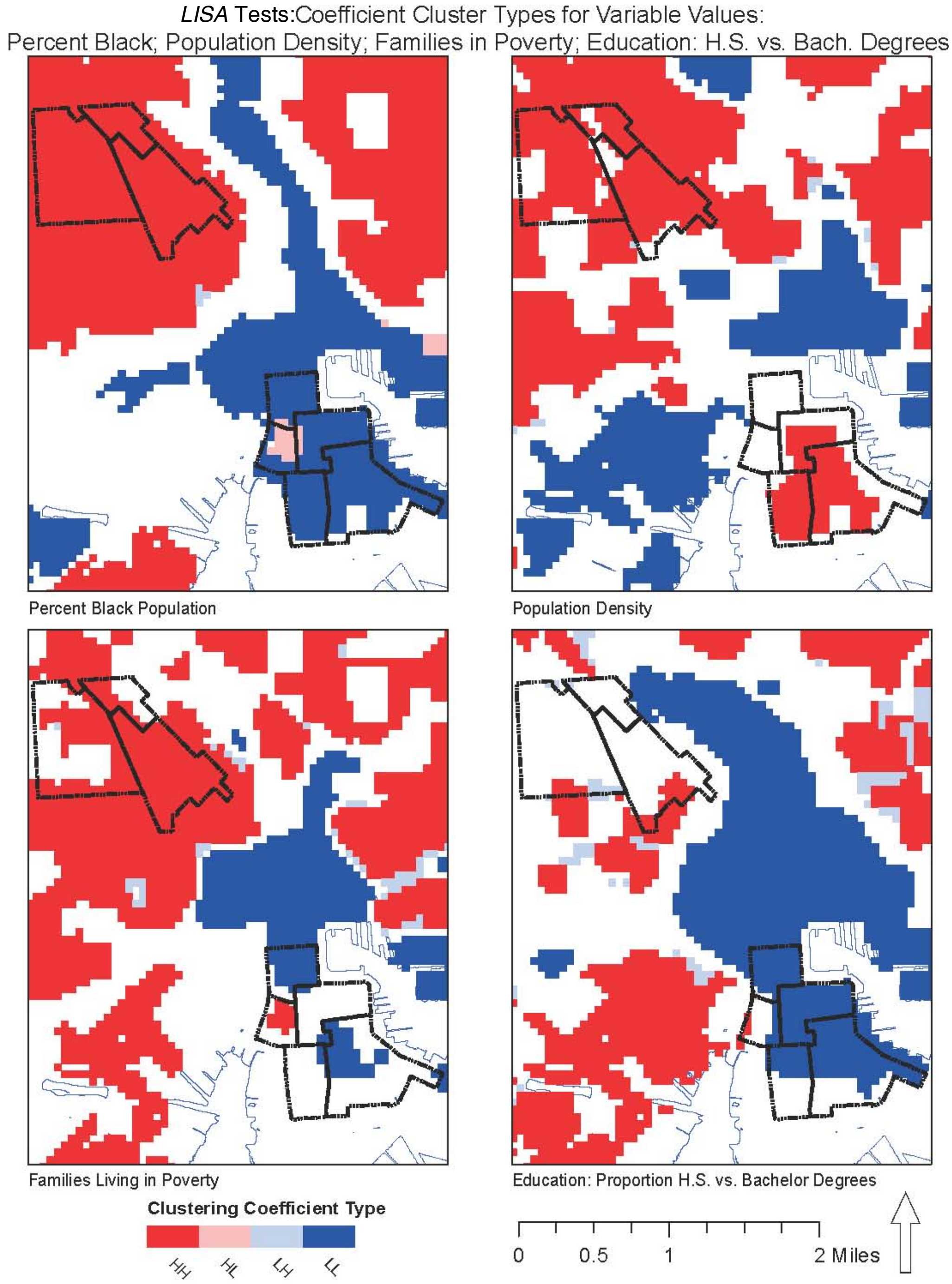

Figure 14 – *LISA* Tests – Coefficient Cluster Types for independent variables, Percent Black, Population Density, Families Living in Poverty, and Proportion of Households with Bachelor vs.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

The final two LISA maps (see Figure 15) show that Sandtown-Winchester has an above average percentage of vacant houses and that this high rate of “vacants” is uniformly distributed throughout the neighborhood space. The Federal Hill map, on the other hand, demonstrates that in the south there are vacants, but not in numbers above the area average, and no pockets of vacant houses. To the north there is a more concentrated cluster of lower than average vacant houses (the blue cells). A similar pattern holds for home ownership measures where in Sandtown-Winchester lower rates are surrounded by similarly lower-than-area average home ownership measures. In the south of Federal Hill, a small patch of red cells however indicates high measures of ownership, higher than area average, surrounded by other homeowners., then it trails off into more average measures surrounding this pocket (the white cells).

Important sub-variables within the aggregated call rate variables demonstrated differences in rates, when viewed separately, and locally. These included “Physical Housing Blight” (Figure 16) where Sandtown-Winchester demonstrated higher than average calls made compared to Federal Hill and had clustering in the west, in particular immediately in the area associated with the Sandtown Habitat community group. “Parking Complaints” were also a problem with neighborhood differences (see Figure 17, below) reported by both neighborhoods but quite different in spatial patterns in each neighborhood: concentrated and high rates of calling near the stadiums in Federal Hill, but dispersed and high rates across all of Sandtown-Winchester. Much higher than average reporting for calls about “Social Disorder (911) Disorderly Person” (Figure 18) occurred in Federal Hill, especially on the west side, nearer the stadiums but no substantive spatial or rate differences appearing as reported on in Sandtown-Winchester.

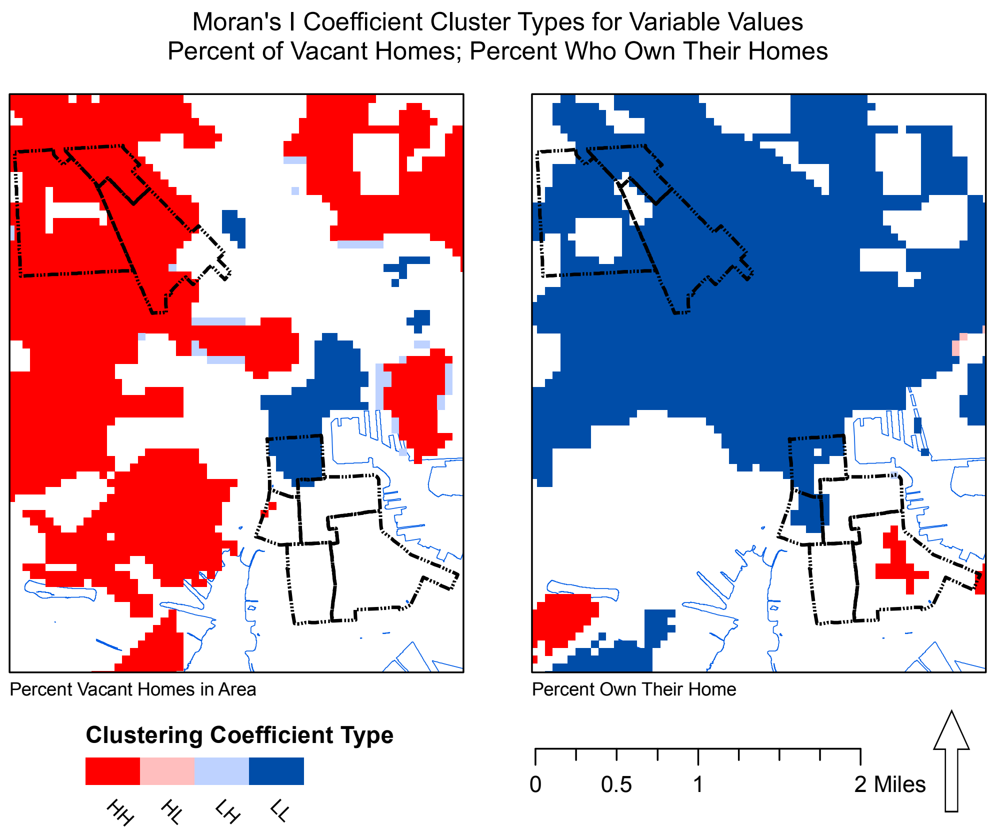

Figure 15 – *LISA* Tests – Coefficient Cluster Types for independent variables Percent Hon *LISA* Tests:**d Percent Who Own Their Own Home**

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

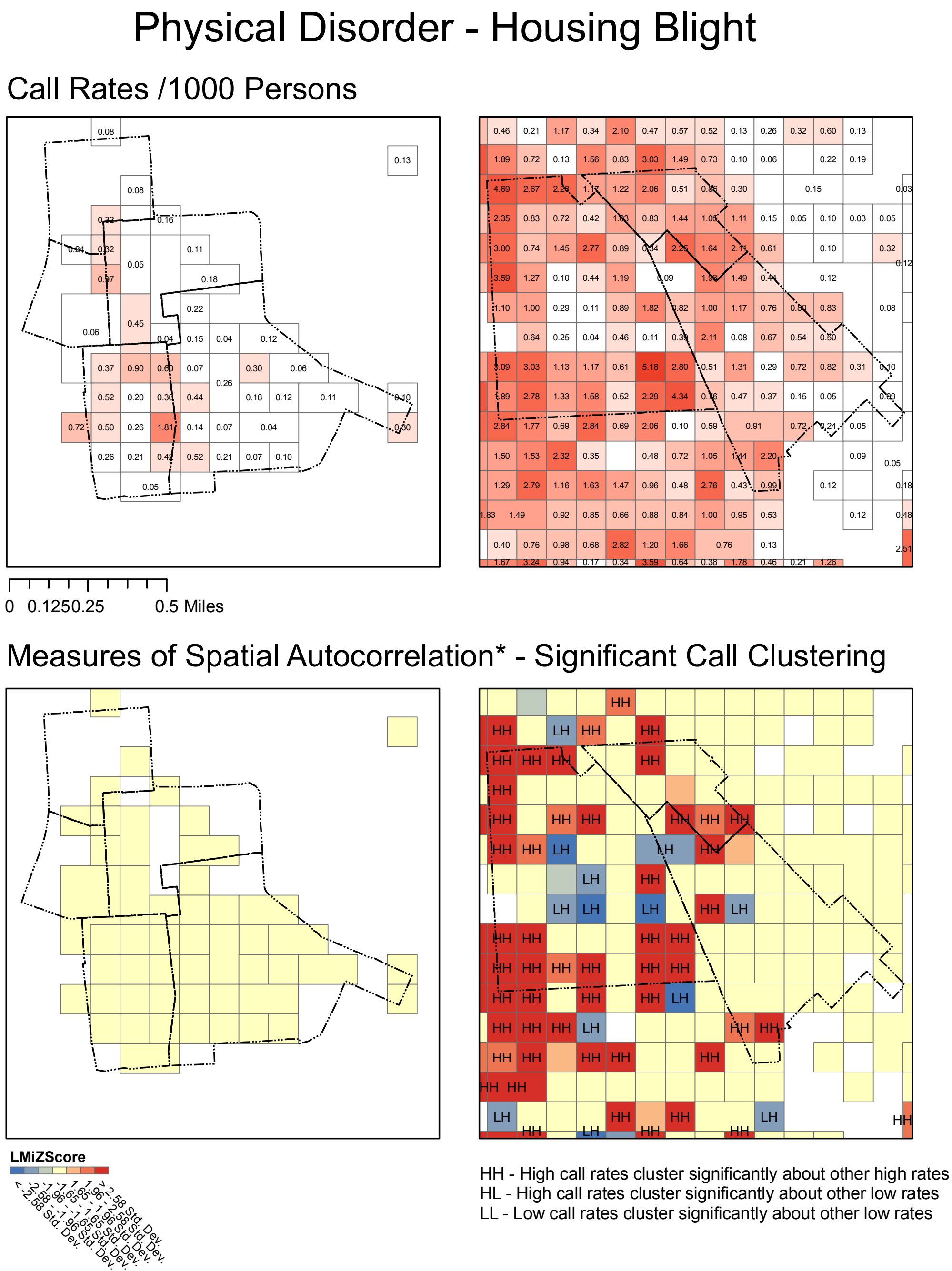

Figure 16 - 311 Calls for Physical Disorder – Housing Blight

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

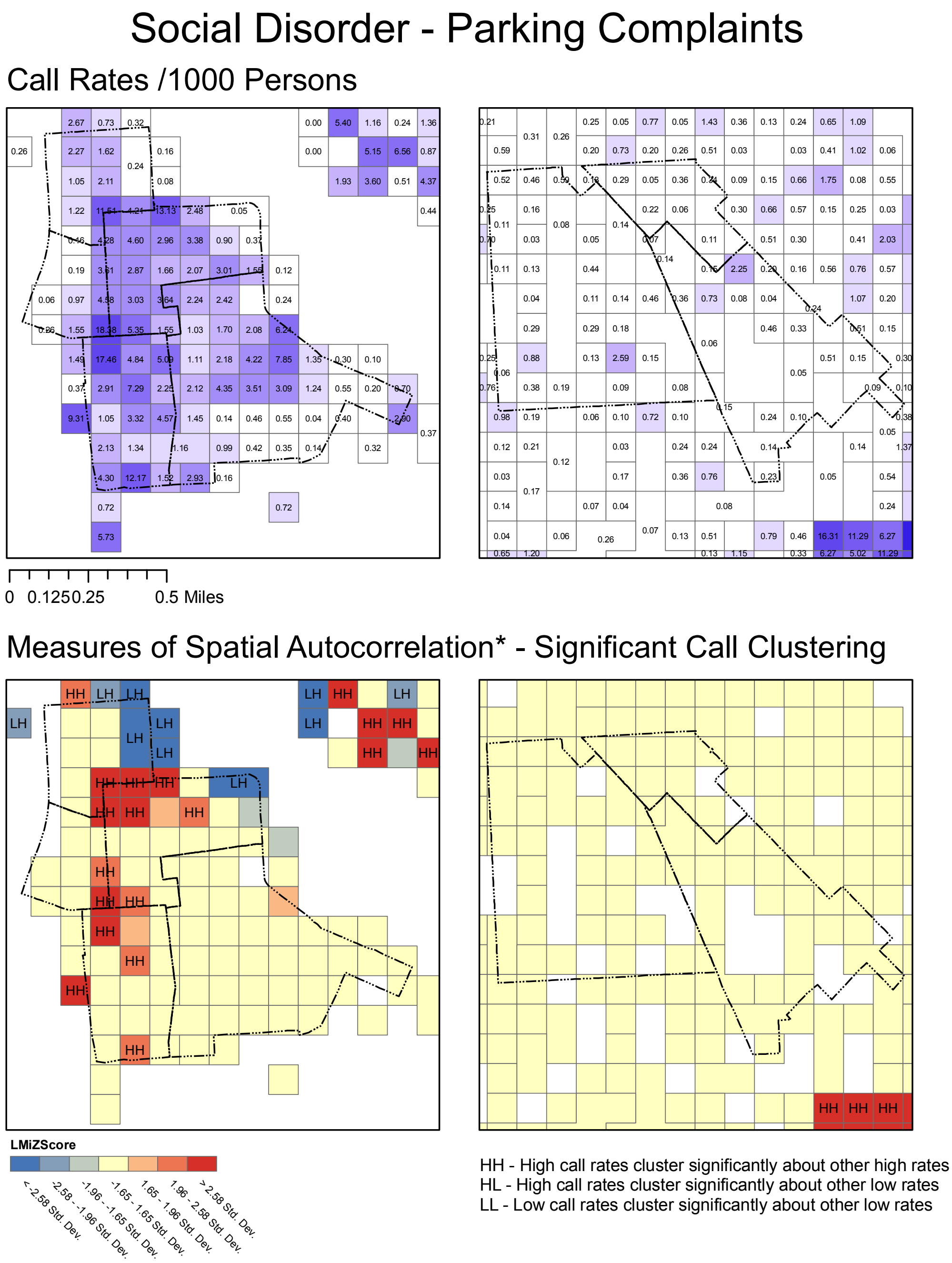

Figure 17 - 311 Calls for Social Disorder – Parking Complaints

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

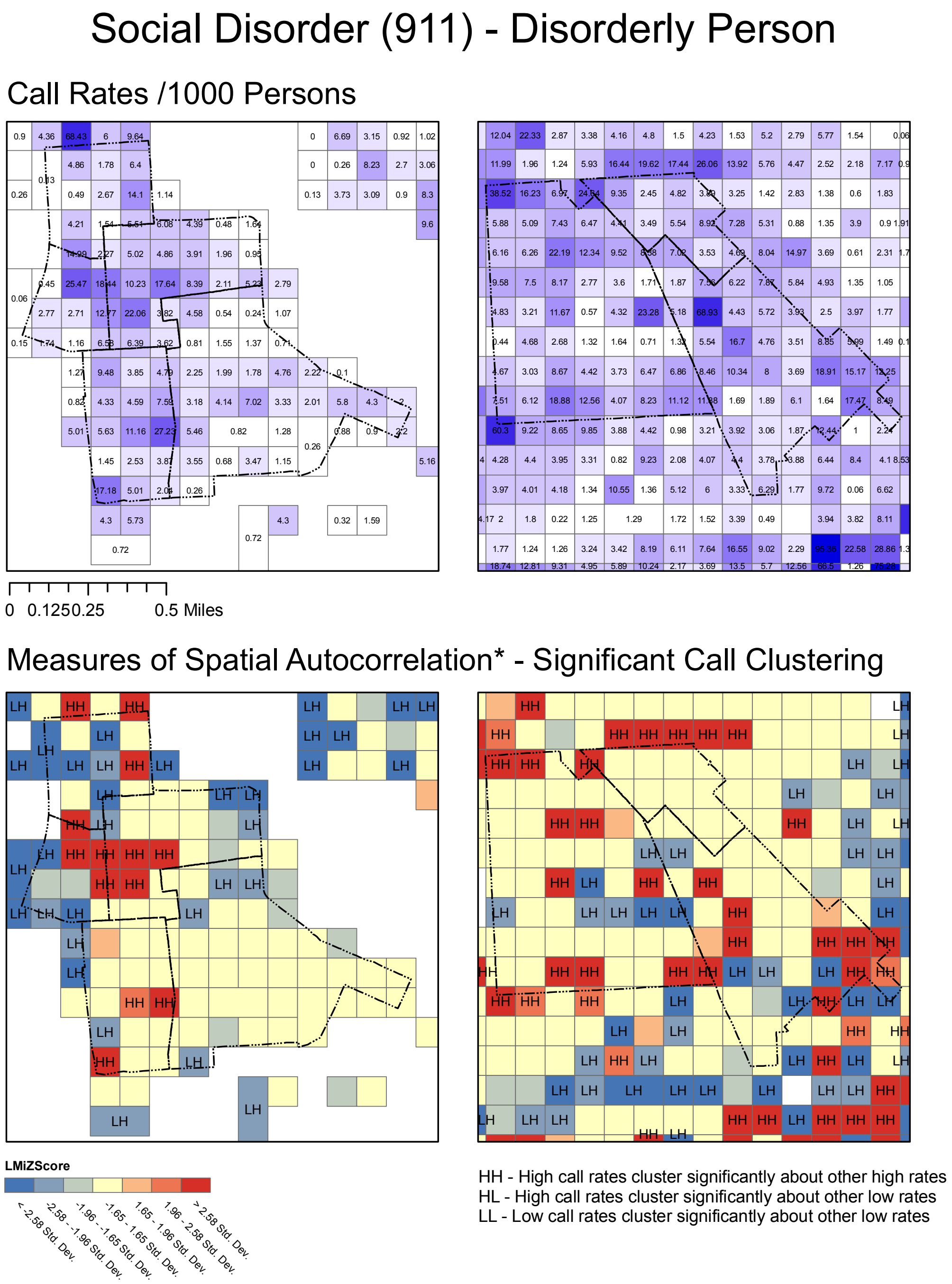

Figure 18 - 311 Calls for Emergency Social Disorder – Disorderly Person

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

The starkest map indicates the differences in rates of calling between the neighborhoods for “Narcotics (Dealing etc.)” problems (see Figure 18). In this map Sandtown-Winchester is all but buried in a sea of red cells indicating the high rates of calls about drugs there, and that those rates are uniformly distributed throughout that space. There is almost *nowhere* in this neighborhood where drug activity does note appear as a problem. However, there is also almost nowhere residents are not acting, calling for assistance, to remediate this issue. Federal Hill, on the other hand, while it still has drug problem calls more closely mirrors citywide averages of call rates with no clustering.

In summary, while some sub-components exhibited clustering that could indicate significant issues when all variables were aggregated the LISA exploration revealed few problems with predictor variables or the normality of their distribution across the neighborhood spaces. There were, not surprisingly, differences *between* the neighborhoods: Sandtown-Winchester is proven to be a fairly uniform neighborhood of black persons with low income, high unemployment, low education, lower than average home ownership, high rates and equally distributed issues of neighborhood blight (as abandoned houses) and higher than average rates of homogeneity (neighborhood cohesiveness), and low residential mobility (stability), compared to the neighborhood and residents found in Federal Hill. Furthermore, the biggest difference in efforts to remediate their local issues shows the dire nature of life in Sandtown-Winchester – a neighborhood blanketed in drug crime and urban blight. While the two neighborhoods report issues with “Disorderly Persons” Federal Hill’s issues are found

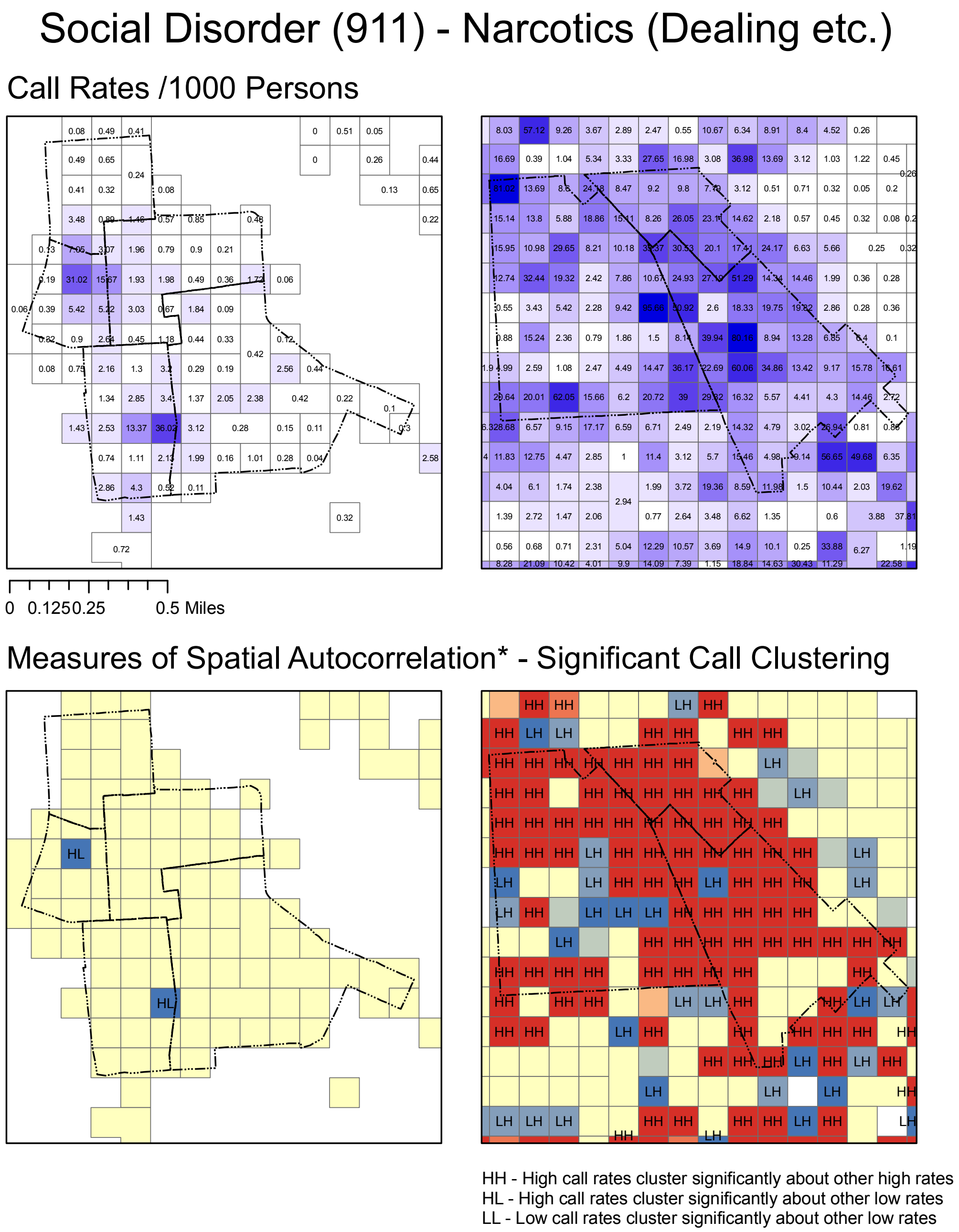

Figure 19 - 311 Calls for Emergency Social Disorder – Calls Reporting Narcotic Use, Dealing etc.

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

nearby the stadiums, and more than likely involve *visitors* to that space, whereas Sandtown-Winchester's violent and disorderly persons are sprinkled *throughout their neighborhood*.

Finally, while Sandtown-Winchester devotes above average energies to drugs and disorderly persons compared to Federal Hill's residents, the latter's neighborhood only divergent focus from citywide norms in calling patterns involves issues about "Parking." It is fair to argue that the social disorders the two neighborhoods are battling have different impacts on the quality of life for their respective residents. It is also germane to recognize that so to are the energies and risks of residents engaged with problem solving and the skills and resources needed to successfully combat these issues. The neighborhoods would appear to experience social disorder than one another, while working to fix their problems from entirely different social means and status positions.

Local Moran's I z-scores: Identifying Statistically Significant Spatial Clusters of Call Rates and Independent Variables

Using the LISA measures provides only a visual tool to generate assumptions about the underlying mechanisms producing variance in call rates by the neighborhoods. To explore whether or not these findings are outside what we would expect normally,– as events occurring for reasons other than chance alone -- we use the statistical test called Moran's *I*.

This calculation generates z-scores across the spatial plane to illustrate the degree to which a variable's *locally-observed* value is in keeping with the normally expected values found around it. These z-score values are then mapped, and color-coded, to visually illustrate *how divergent* locally reported values are from the expected values. When large clusters of the same extreme z-scores appear together, they indicate something fundamentally different in that area is driving scores. Ideally, on a visual map, each observation as tested should end up "white" on that map. Dark blue on a map depicts negative *z*-scores in excess of -2.51, white is the "zero point", and finally dark red indicates positive *z*-scores in excess of 2.51. We not only expect each score to be normal but also the distribution of values and their spatial *dispersion* to be *randomly distributed*. However, data *does* cluster in space and mapping the z-scores then provides the ideal opportunity to identify zones of clustered *diverging* values – in this case call rates, or independent variable values – as spatial outliers when those cases exhibit values very different from their neighboring values (Haining, Wise and Jingsheng 1998). The following results explore differences between the two neighborhoods' reported call rates to learn if we can reject the null hypothesis that there is <u>no spatial clustering</u> of calling rates. Reviewed first are maps of the dependent variables, aggregate call rates for the three models and 911 Crime calls, followed by the input, independent variables.

Reviewing the maps generated with Moran's *I* measures testing "311 Calls for Physical Disorder" (see Figure 20, top left) rates for clustering the mapped z-scores do exhibit some extreme values, indicated by the dark red, and some dark blue cells. These cells are found mostly found along the major arterial corridors There are clusters of blue squares to the south of Upton (the eastern neighborhood of this set here) indicating statistically significantly *lower* the call rates for Physical Disorder. This stands to reason as this area holds many newly renovated row homes along George, Jasper and Paca streets..

A significant difference between the two neighborhoods appears when testing call rates made concerning calls for social disorder (see Figure 20, top right). Federal Hill's mapped scores indicate *significantly higher* rates than would be expected in almost <u>all</u> of this neighborhood while Sandtown-Winchester's rates are within normal expectation bounds. Federal Hill. The exceptions in Federal Hill appear to be Sharp-Leadenhall, to the west, and Otterbein to the north which both have proportionately far more public housing residents, more African Americans, more unemployment, and more poverty than the central, eastern and almost exclusively white, area of Federal Hill.

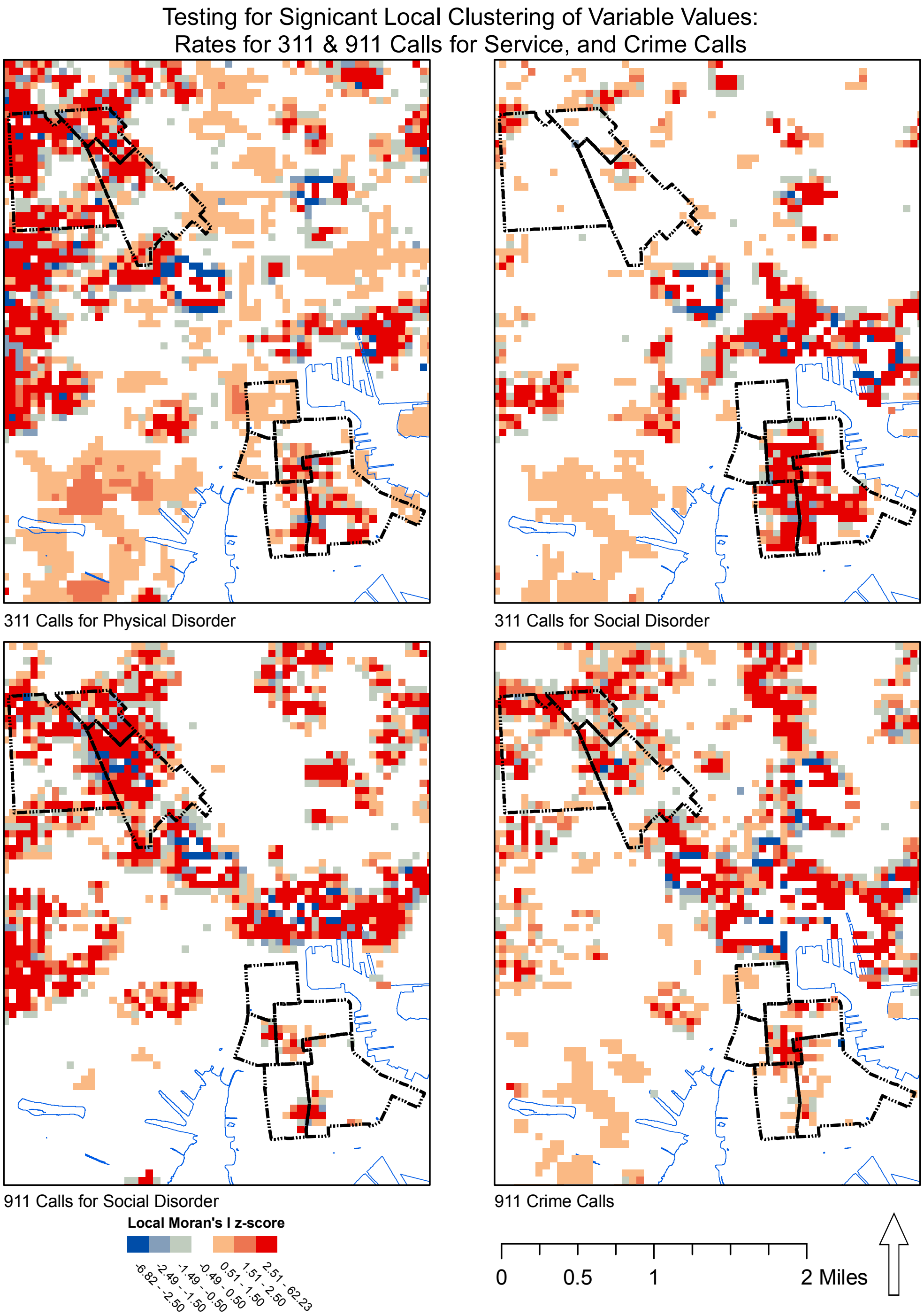

Figure 20 – Identifying Significant Spatial Outliers for Dependent Variables, Call Rates, using Moran's *I* *z*-scores

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

Reviewing results of the mapped z-scores for emergency social disorder call rates it is Sandtown-Winchester that demonstrates statistically higher, and clustered as such, calls being made about violence, abuse, threat and so forth, compared to Federal Hill. 911 Crimes Call calling rates are fairly uniformly distributed throughout both neighborhoods. In the heart of Federal Hill, at Cross and Ostend streets, there is a small cluster of higher than expected call rates. With Raven's Football Stadium just to the west of this intersection this area is filled with bars, businesses and restaurants frequented by game attendees before and afterwards. The Sandtown-Winchester area displays a similar pattern of higher rates primarily along well-traveled corridors in northern Upton, but also along North Avenue. What is striking in Sandtown-Winchester is that it reveals that their calling pattern *is* statistically significantly *higher in rate* when calling about emergency crime problems compared to Federal Hill (see Figure 20, bottom right).

Next are brief discussions of the Moran's I tests and mapped *z*-scores testing for statistically significant clustering of the independent variables measured values. A caveat first: One should exercise caution interpreting variable *z*-scores. The *color* of the mapped clusters is not as important as knowing the color's *meaning* in relation to the variable's local context as mapped z-scores can display *the same clustered color values but have opposite meanings*. For example, in the income variable, top left map (Figure 21) the measures tested, and then mapped as *z*-scores, result in clusters of red in *both* neighborhoods indicating statistically significant shifts from the local mean norm expected. However "on the ground" we know in Sandtown-Winchester it indicates a substantively increasingly *lower* income compared to the area mean while in Federal Hill

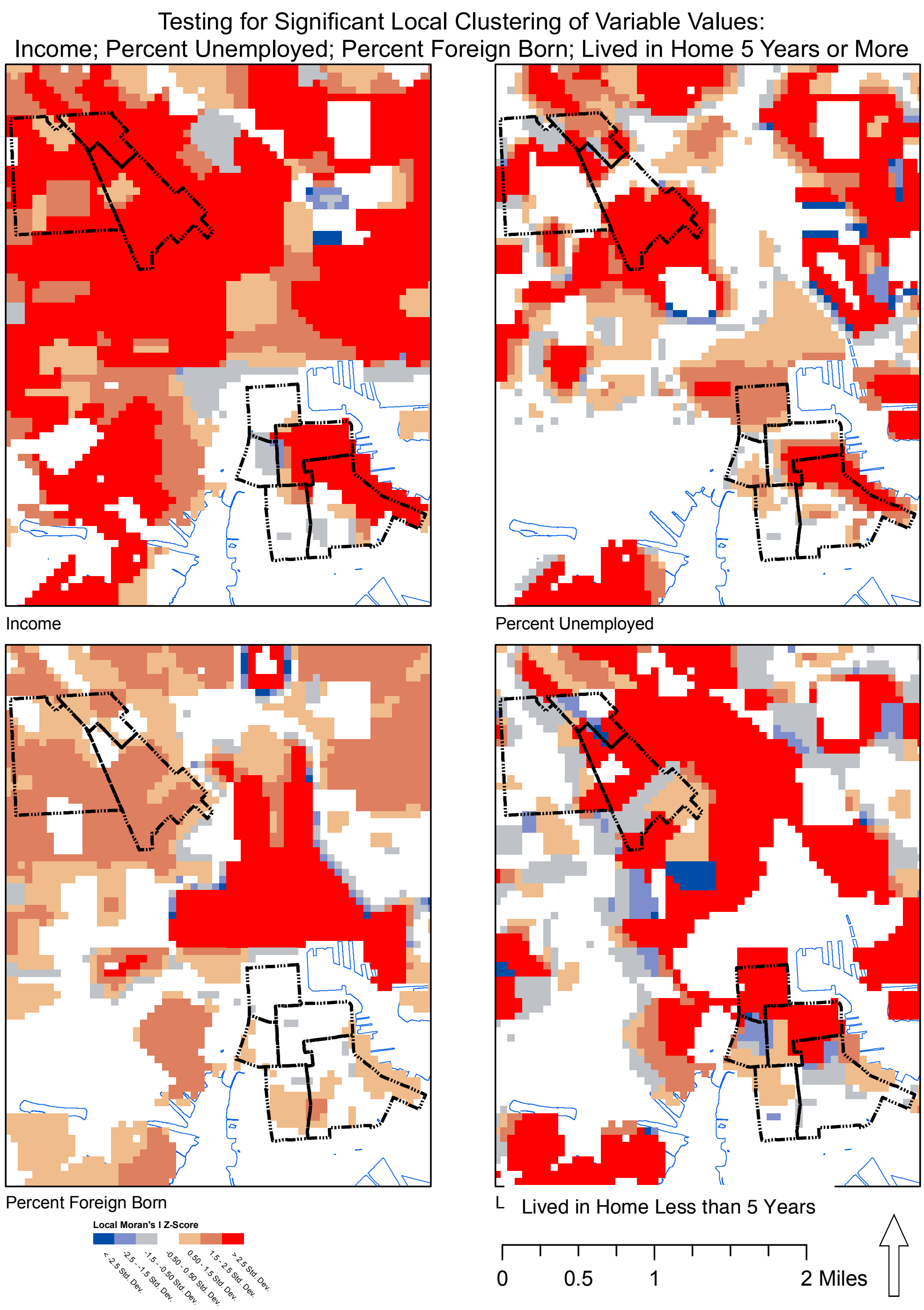

Figure 21 - Identifying Significant Spatial Outliers – Moran's *I* *z*-scores – Independent variables, Income, Percent Unemployed, Percent Foreign Born, and Lived in Home Less Than 5 Years

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

it depicts a statistically significant cluster of *increasing* income measures, compared to their own local mean income, something. most evident along the eastern side of the Federal Hill neighborhood where the "super-rich" inhabit the multi-million dollar, exclusive real-estate of the Ritz-Carlton condominiums project. Same color, indicates similar differences but fundamentally different meanings.

The variable "Unemployment" significantly clustered with higher would be expected in southern and northern areas of Sandtown-Winchester (see Figure 21Figure 21, top right). In Federal Hill however, unemployment measures significantly lower from the area means, again in the richest, northeast area. "Percent Foreign Born" (Figure 21, bottom left) is evenly spatially distributed, and no significant clustering. For "Lived in Home Less than 5 Years" the significance maps are mixed: some areas of Federal Hill show display statistically higher than expected measures of persons living there less than 5 years in the north while the same is true of the east side of Sandtown-Winchester. "Percent Black" population (Figure 22) displays spatially uniform and statistically significant higher percent of black population in Sandtown-Winchester while significantly lower in Federal Hill. One exception remains as the patch of blue, in Federal Hill for the largely black residential population in public housing projects. Population density is equally high compared to area means while "Percent Families Living in Poverty" shows statistically significantly higher rates in the observed cluster in Sandtown while any observed LISA clusters in Federal Hill are found, with this test, to be not statistically significant outlying values. The variable measuring education level shows marginally strong, significantly higher education levels in Federal Hill, compared to their surrounding neighbors.

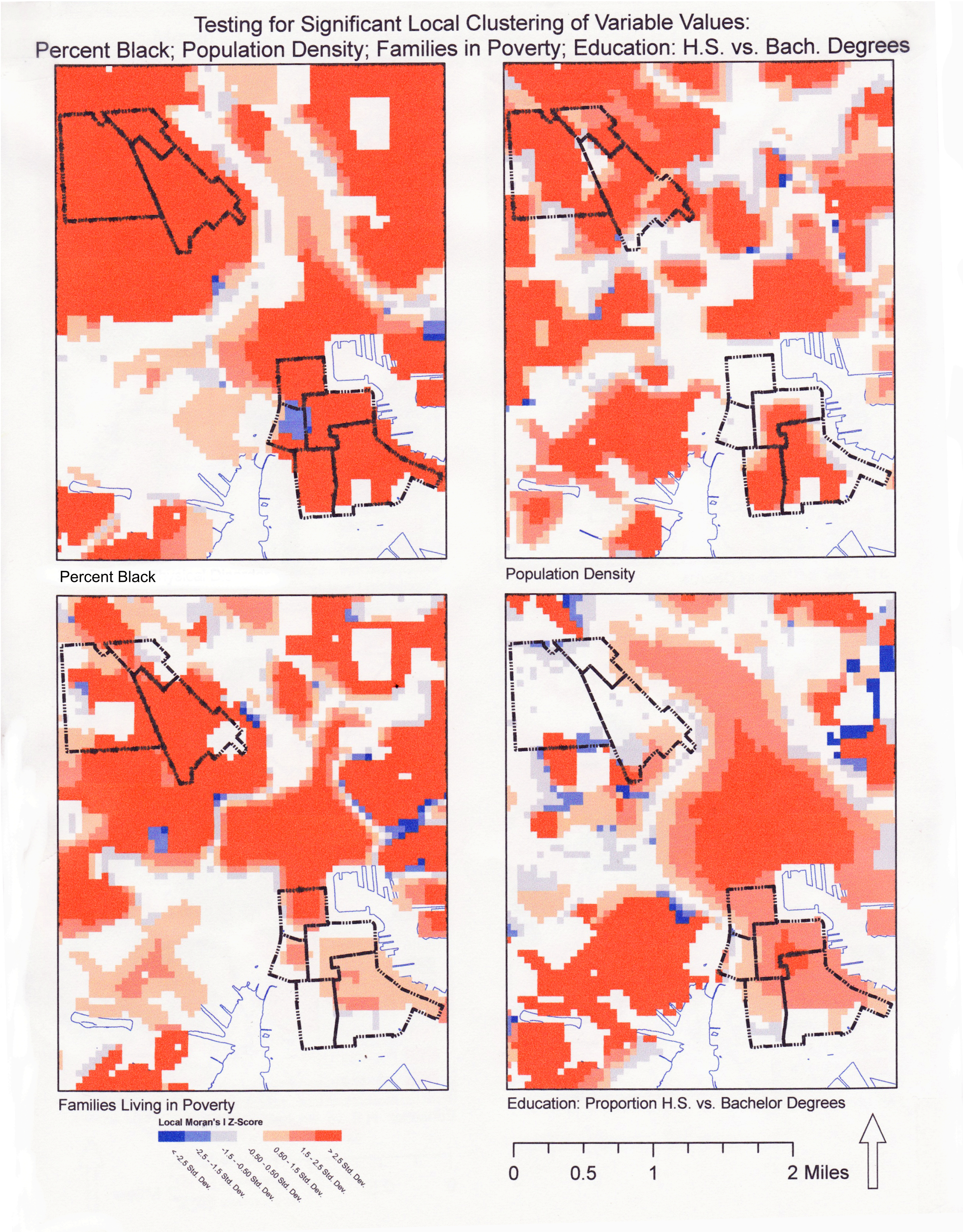

Figure 22 - Identifying Significant Spatial Outliers – Moran's *I* *z*-scores – Independent variables, Percent Black, Population Density, Families Living in Poverty, and Proportion of Household with Bachelor's versus High School diplomas.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

Finally, “Percent Vacant Homes” demonstrates statistically different and outlying measures of “vacants” in Sandtown-Winchester while in Federal Hill measures are not seen as out of the norm, and are, in fact, largely insignificant. The same spatial trend extends to home ownership with significantly lower measured values in Sandtown-Winchester. The final series of maps that follow explore briefly if outlying values detected with the Moran’s I tests are clustered into significant spatial groupings.

Testing for Significant Spatial Clustering of Model Variables

Above I first used LISA measures – local indicators of spatial autocorrelation - to determine the spatial structure and spatial patterning of data observations (Anselin 1998, Anselin, Syabri and Kho 2004) and then Moran’s *I* z-scores to help uncover divergence of observations from the local, expected mean. But Anselin (1998) notes that while we can identify cluster patterns using exploratory spatial data analyses, i.e. with *LISA* and Moran’s *I* measures, the maps only display differences (or similarities) in the observed and mapped values but not whether they are *locally* dependent on other values. The LISA maps <u>suggest</u> dependence may be present, and the *z*-score tests prove outliers exist, but how do the relate? How do we test those outliers are *statistically significant* clusters? The final results show whether the model variables have any underlying spatial structure of significance. beyond “chance” alone. Using Moran’s *I* statistic *p*-value outputs, and mapping those, we can display the significantly clustered spaces. Statistical strengths are demonstrated using color, with the strongest clustering significance indicated with bright green clusters (p-values < 0.001) followed by pink-colored clusters (p-values of <0.01) and finally magenta-colored clusters where p-values are <0.05).

Tests for Significant Clustering of Dependent Variables, Calls for Service Rates.

Referring to Figure 23, looking at rates of 311 Calls for Physical Disorder, there is some significant clustering in the northwest area of Sandtown-Winchester – in the area of the Sandtown-Winchester community organization offices, and much more marginal clustering in south Federal Hill. For 311 Calls for Social Disorder there is definitely a significant cluster of higher rates in Federal Hill with nothing appearing in Sandtown-Winchester. The reverse if true when analyzing clusters for 311 Emergency Social Disorder calls -- Sandtown-Winchester's elevated rates are definitively not happening because of chance alone. 911 Crime Call rates showed no significant clustering.

Tests for Significant Clustering of Independent Variable Measures.

Referring to Figure 23 through Figure 26, the initially-identified cluster patterns found using *LISA* tests held up as statistically significant clusters, with variable measures that were statistically significantly identified as outliers, compared to the local area means with the Moran's I *z*-scores, when the *p*-value mappings were done. In other words the clusters initially identified as probably different neighborhood spaces *are revealed as two, distinctly different neighborhood spaces.* And this was not only evidence of aggregate data differences between the two -- those traditional research measures averages, rates etc. --but also spatial tests that substantiated that the neighborhoods were *spatially distinct* locales as well; clustering was generally pervasive and uniform across each of them for a given variable. For example independent variables, like "Percent Population Black" were, not surprisingly, found to produced clusters in of high representation in Sandtown-Winchester (almost entirely black by census data) and clusters of *low* representation in Federal Hill, which is almost entirely occupied by white residents. However, what about cases where clustering was found, but only in one locale?

Perhaps the most intriguing results here are evidence produced for variables with strong outlier values *and* statistically significantly spatial clusters that appear within one neighborhood but not the other. It raises the question whether the variable's values were not important to the model perhaps or they were impacted by, affected differently, in that space by some, as yet unspecified, mechanism. In addition, when a variable appears as significantly clustered within one neighborhood, but not the other, we say it is spatial autocorrelated versus spatially independent. As such that variable is suspect in the model as it violates formal statistical expectations of randomness of observations (Maantay and McLafferty 2011) since observations that are random in *only one* neighborhood clearly make it *not randomly distributed* entirely, and hence problematic.

In this project seven variables displayed such exclusive spatial characteristics - significant measures and clustering exclusive to one neighborhood (see).. Five of these were found in Sandtown-Winchester as "Rate of 311 Emergency Social Disorder Calls", "Percent Foreign Born", "Percent of Families Living in Poverty", "Percent of Vacant House", and the "Percent Who Own their Own Home." In Federal Hill "Rate of 311 Social Disorder Calls" and "Education" both demonstrated measures outside the statistically expected values. Most importantly perhaps is that while independent variables indicate misspecification more generally the exclusivity of two of the three different call rate prediction models' *dependent variables*, and one of them in each of the two neighborhoods, adds additional support to the idea that

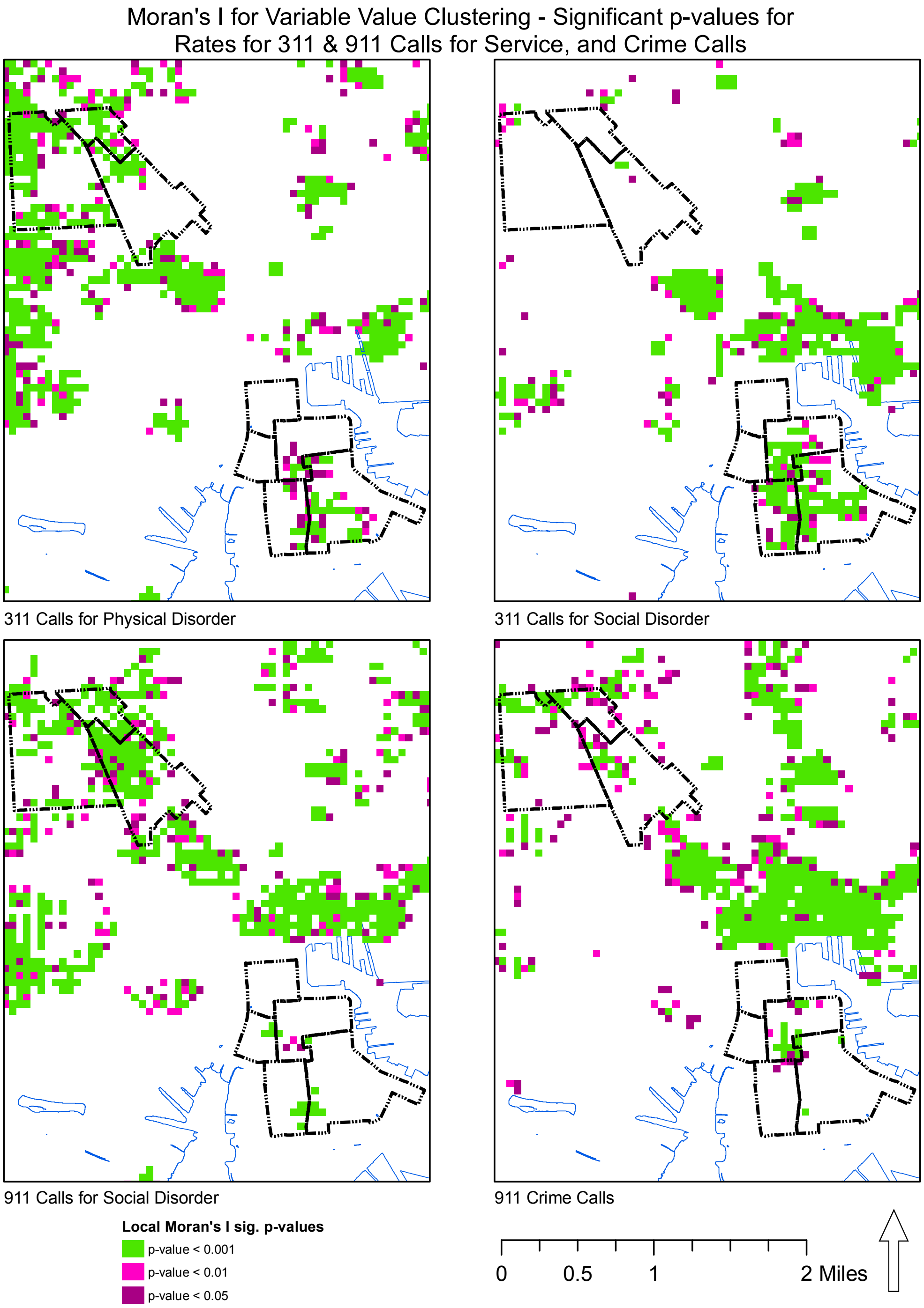

Figure 23 – Moran's *I* - Mapped *p*-values, tests for significant spatial clusters, dependent variables, Call Rates

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

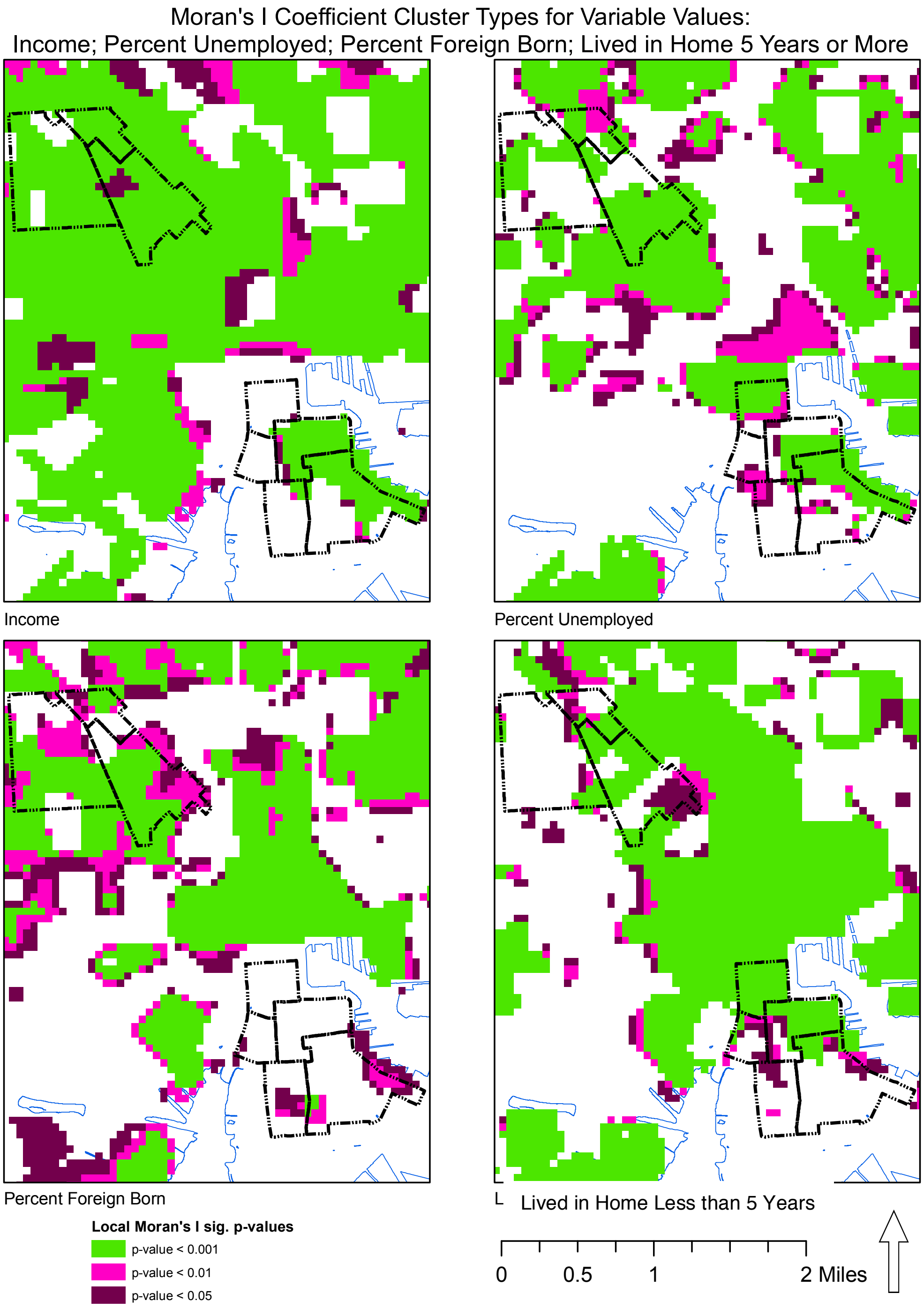

Figure 24 - Moran's *I* - Mapped *p*-values, tests for significant spatial clusters, independent variables, Median Income, Percent Unemployed, Percent Foreign Born, and Lived in Home Less than 5 Years

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

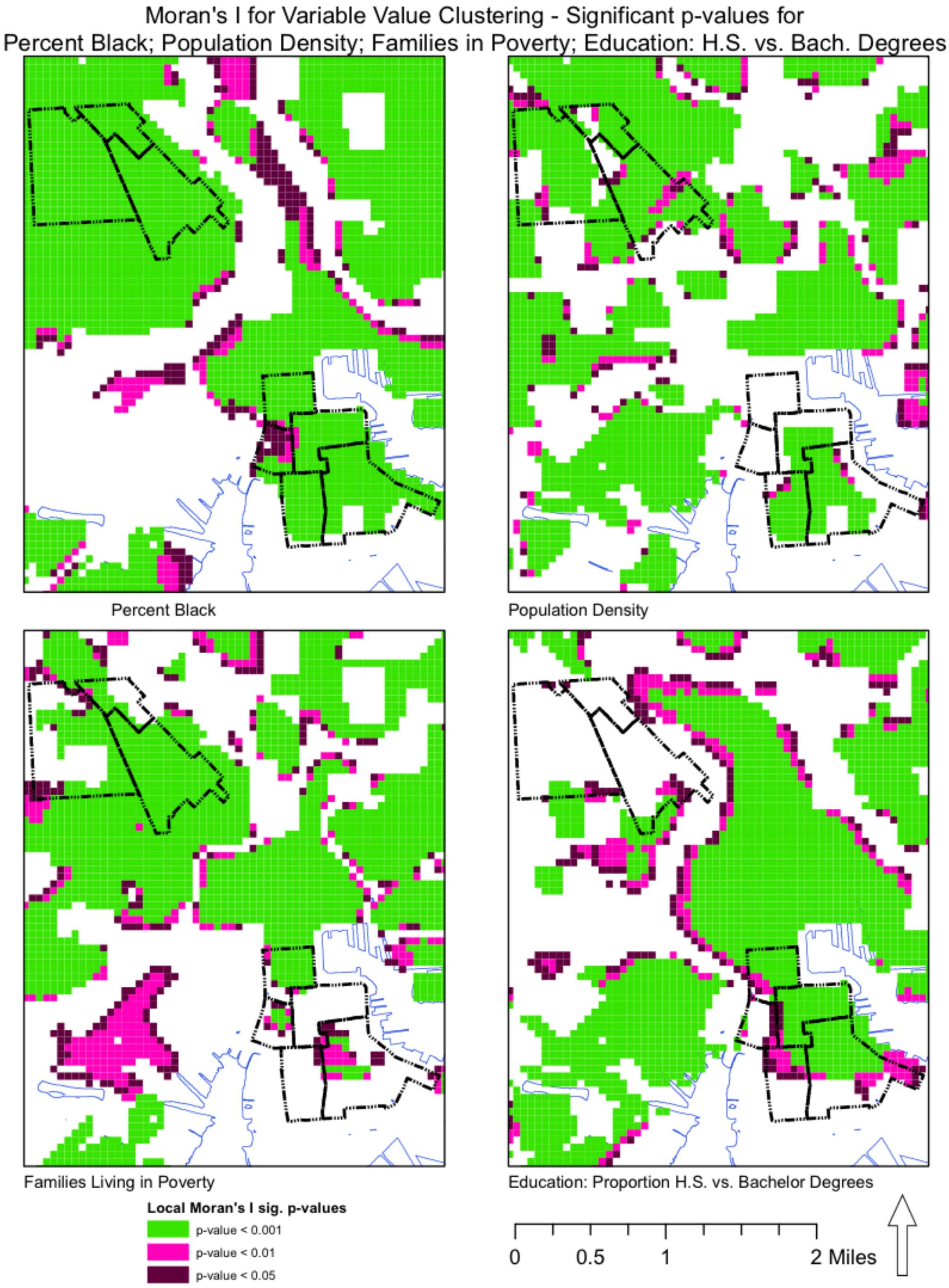

Figure 25 - Moran's *I* - Mapped *p*-values, tests for significant spatial clusters, independent variables, Percent Black, Population Density, Families Living in Poverty, and Proportion Households with Bachelors vs. High School Diploma

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

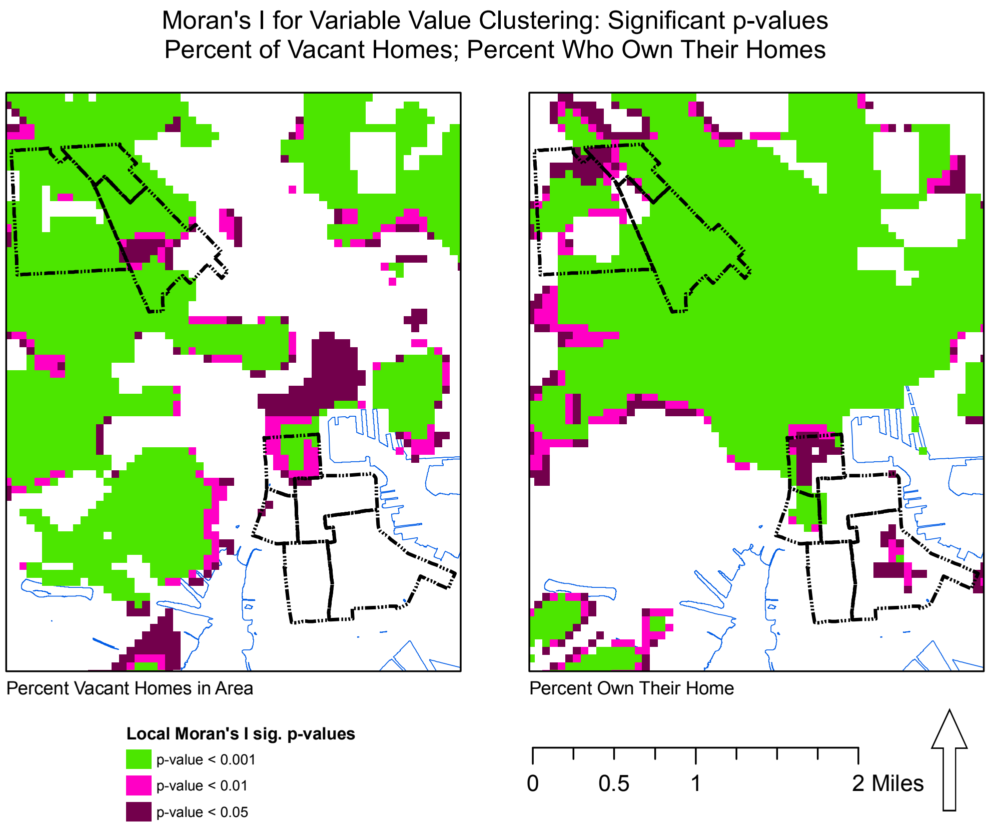

Figure 26 - Moran's *I* Mapped *p*-values, tests for significant spatial clusters, independent variables, Percent Vacant Homes, and Percent Own Their Own Home.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

these particular calling rates (and hence resident behaviors to call) *are* impacted differently within each neighborhood.

OLS and GWR Results

As stated at the outset of this project, I wanted to explore the power of a multi-variate, spatially-sensitive statistical approach that is still relatively unknown to most sociologists (Coulton 2012, Dietz 2002, Entwisle 2007, Gieryn 2000) with some sociologists going so far as to say we are guilty of neglecting space altogether in our research(Lobao, Hooks and Tickamyer 2007). This project treads on some newer ground then and I want to maintain the focus on results, rather than methodologies. I provide detailed discussion of those methods and results in Appendix II presenting detailed discussion of the steps I took to do this, and maintaining consistency with what is prescribed by those skillful at using spatial analyses, and specifically geographically weighted regression. Rather than report a large number of individual findings, here, I summarize these things in a way that is consistent with my more descriptive analyses already reported. Thus I discuss, very briefly, between- and within-neighborhood results when looking with considerable care at how one type of call rate may be related to another. I had stated much earlier that this part of my project was exploratory and it is, thus my decision to summarize these results here and provide more detailed discussion in the appendices.

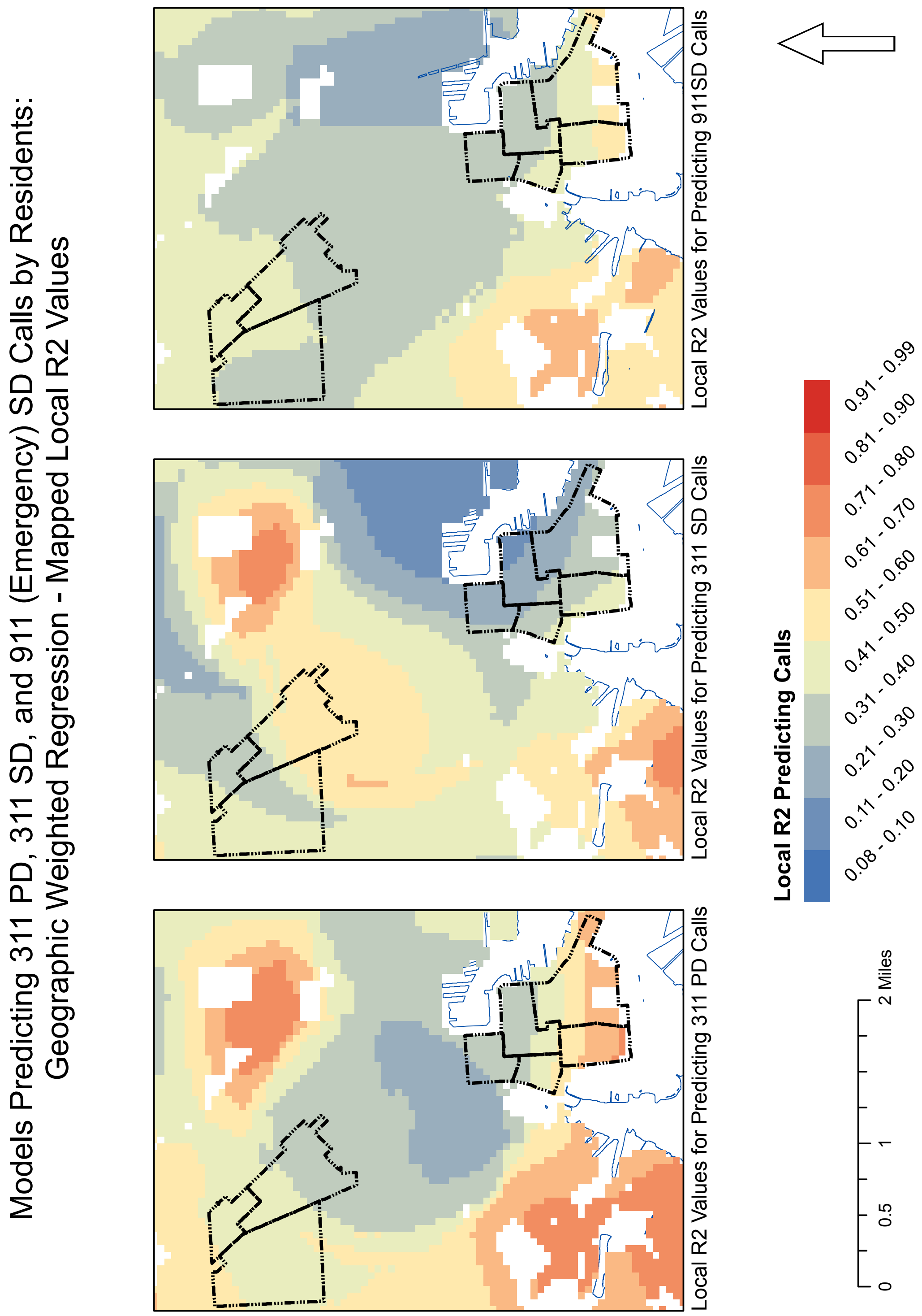

Figure 27 – Models Predicting Calls for Service Rates: 311 Physical Disorder calls, 311 Social Disorder calls, and 911 Emergency Social Disorder calls -

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

For the GWR results, speaking globally first, and comparing from one prediction model to the next, within the different call types, there is significant prediction strength for each model. Also high variance of that strength internally, within the two neighborhoods, when predicting rate changes of “311 Physical Disorder Calls” when using the variables chosen as proxies for local social and physical disorder. Strength of model prediction is the lowest using these parameters when predicting changes to rates for “Emergency Social Disorder Calls” and, here, spatially the most uniform across both neighborhoods. Finally, prediction of “Social Disorder Calls” is better predicted when looking at the Sandtown-Winchester neighborhood, compared to Federal Hill. Variance in unemployment and population density had no measureable effect on call rates.

Within neighborhoods Sandtown-Winchester’s call rate changes, specifically increases in those rates, happen for more of the “wrong reasons” than the “right” ones; variables indicating increases in local area families in poverty, mean area income, and decreases in education levels and violent crime dominate the influences increasing calling there. Only “Emergency Social Disorder Calls” rise when median income in Sandtown-Winchester goes up, though it is not clear this is a positive outcome either.

The reverse is true as well for suppression of rates in the poorer, Sandtown-Winchester neighborhood: when crime rate is high calling goes down. Increases in local diversity, shorter tenancies and home ownership rates also contribute to lower calling volumes. In addition, Federal Hill’s calling predictions are running opposite these observations regularly in the results. Federal Hill’s call rates are increased by the presence of foreigners, home ownership rate, and residential stability, fundamentally *positive* stimuli that appear to encourage engagement. The only negative stimuli that prompt more calling behaviors appear to be increases in physical disorder call rates themselves (what that correlation might be is unclear, but possibly spurious) and violent crime rates.

The variables for income, population density and education provided little explanatory contribution overall. Unsurprisingly were positive associations noted between measures of physical disorder (vacant houses, for example) and increases in calls for physical disorders. However, homeownership did stand out as *not* contributing to increasing surveillance about the physical neighborhood. Increases in rates of calls made about general social disorder are positively linked to increases in physical disorder calls themselves – for every tenfold increase in physical disorder calls there is doubling of calls about social disorder.

Measures of social disorder like neighborhood instability and homogeneity (Lived in Home Less than 5 Years, Percent Foreign Born, Percent Black, Families Living in Poverty etc.) were found to suppress call rate changes concerning issues about physical and social disorder generally. “Percent Black” predicts increases in calls about physical disorder when higher while neighborhoods with are higher proportion of black persons also are predicted to call *less* about social disorder whereas emergency social disorder remains increased in the presence of the race variable. And while “Families Living in Poverty” was associated with decreases of residents making calls about social disorder there is a significant effect on call increases for “Emergency Social Disorder”: for ever 1% increase in poverty-stricken families we can predict a 5% increase in emergency social disorder call rates. Violent crime call rates are also very strong, across all models, in predicting rate increases of those other call types. The strengths of the coefficients are discussed extensively in the appendices (see Figure 36 through Figure 39).

Support for Hypotheses

The hypotheses are described in detail in the appendices (see 292) but are briefly noted here. The first two hypotheses proposed the wealthier neighborhood of Federal Hill would demonstrate increased calls to address social and physical disorder issues and that there would be an offset – as wealth increased a shift from physical disorder social control mechanisms to social disorder ones would occur. I reject the first as results showed Federal Hill consistently engaged at *lower* rates of calling than poorer Sandtown-Winchester in almost every, single one of the call categories (and calls were population adjusted). The second hypothesis is rejected partially because there was disproportionate effort to curtail social behaviors in Federal Hill that were simply not happening in Sandtown-Winchester. However, overall, Sandtown-Winchester calls about social disorder issues *sixteen times* as much as Federal Hill.

I fail to reject the third hypotheses – that call rates about physical disorder (*H3A*) and physical disorder (*H3B*) would be suppressed more when physical and social disorder measures were higher. *H3B* is rejected tentatively, however, as there does appear to be some connection to *increases* in particularly "Emergency Social Disorder" when the disorder indicators themselves increase – disorder begets more disorder in some cases.

Hypothesis 4A, noted I expected to see less clustering of “High + High” or “Low + Low” cluster patterns of call rates in the maps produced. It was not rejected when predicting changes in “311 Physical Disorder” and “311 Social Disorder” calls but *is* rejected when predicting changes in “Emergency Social Disorder” calls by the social and physical disorder indicator variables since there were unexpected clusters of rates in Federal Hill where I expected to see less - expecting a more unified social normative environment. The final hypothesis tested for the effect of social and physical disorganization on the predictor variables themselves – expecting their explanatory power to be much more, spatially, fractured and inconsistent. This was the case and the hypothesis was not rejected.

These findings and hypotheses outcomes are consistent with the descriptive findings noted early on. The specific directions and grouping of negative and positive stimuli that appear to operated in the neighborhoods in sometimes reverse manners lends additional credence to the idea that while they are near one another in space they are miles away in lived, spatial, realities. Sandtown-Winchester is, demographically, a kind of caricature of the “inner city” -- poor, almost all-black, low levels of education, high levels of poverty, vacant housing, unemployment, drugs and violent crime. Federal Hill, by contrast, is the caricature of the gentrified, yuppified, Bourgeois “new city” – relative affluent, almost all-white, high levels of education, low levels of poverty, vacant housing, unemployment, drugs and violent crime. In addition, the calling behaviors witnesses support this further. We might say that Federal Hill is where people *want* to live; Sandtown-Winchester is where people *have* to live. I will return to this last comment in my closing discussion to explore why Sydney Brower’s “choicefulness” concept (Brower 1996) is important to consider here when trying to understand local ability to act.

DISCUSSION

This research set out to explore how social disorganization and physical disorganization in neighborhoods affect the actions of their residents, how those residents try to address and indeed alter those spaces, and which social and physical nuisances draw more or less attention. Two clusters of neighborhoods--similar in geographic size and density/types of housing but very different in terms of racial and socioeconomic composition--were compared to explore how responses to experienced incivilities might be governed by local norms and social expectations. As well, measures of local social and physical disorder were used to predict how such disorganization affects patterns of resident engagement with these issues. Both neighborhoods are in central Baltimore. The first, comprising Sandtown-Winchester, Druid Heights, and Upton, represents a locale that is very poor, in deep urban decay, and populated almost entirely by African Americans. The second, comprising Federal Hill, Otterbein, and Sharp-Leadenhall, represents a space that is almost entirely people by a white, affluent, and educated gentry.

Previous research on neighborhoods and other social spaces inadvertently concealed subtle factors that shape local actions. Often using aggregate data, this research did not include the influence and qualities of local, lived-in space on persons' or communities' actions. More traditional research approaches, those not invoking space as an important social influence, often assumed the independence of variable influence on other variables and within the studied sites. As an alternative approach, I employed spatial analyses, testing the 'traditional' ordinary least squares (OLS) linear model, which generates results as global, aggregated parameter estimates, against a geographically weighted regression (GWR) which generates subtle, local measures. Rather than assume the independence of parameter estimates across space, the GWR assumes that spatial differences in locality will, in fact, influence observations, violating the OLS assumption of data-point independence. I examined how physical space and the social experiences of living within it (and all that entails: crime, racism, unemployment, physical decay etc.) might impede or encourage actions in these spaces, measuring how two neighborhoods do and do not respond to these lived-in environments.

To investigate these issues, I identified "calls for service"–requests made by residents in these two Baltimore City neighborhoods requesting remediation about social and physical environment problems in their neighborhoods--as my dependent variable. The entire volume of calls was subdivided into three specific dependent variables, adjusted by populations to generate "call rates." The first model's dependent variable,311 Physical Disorder Calls, was generated from complaints made about a neighborhood's physical environment, its "physical disorder," This included calls about abandoned houses, roadway problems, dirty streets, as well as more nuanced, physical environmental aspects such as lighting problems, overgrown weeds, trash, and graffiti. The second dependent variable, 311 Social Disorder Calls, was generated from calls about social offenses, such as loud noise, drunk persons, drug dealing. The third variable, 911 Social Disorder Calls, was also social, but comprised calls made about residents' perceptions that something violent or threatening was in progress and in need of immediate action or remediation. These three models' dependent variables were regressed on census demographic measures, variables chosen to represent social and economic capital, to see how changes in call rates were impacted by local social and physical disorder and if demographics themselves played a part predicting changes in call rates in the three models.

I first tested each call-rate change model by using non-spatial, OLS linear regression, which generated global coefficient statistics illustrating the influence of each variable on the rate. This method assumed any variable was independent of any other local variables and that local spatial differences did not affect those values. Secondly I re-ran the three models, but this time used a Geographical Information System (GIS) and spatial statistical analyses to determine if spatial dependency of variables existed--clusters or patterns of dependent variable values and call rates that required adjustment/weighting due to local influences on those values by other nearby variable values. Using Geographically Weighted Regression (GWR), I then generated local coefficient values, versus OLS global indicators, for each of the independent variables. The coefficient outputs were then mapped, across the two neighborhood spaces chosen, to illustrate whether or not demographic variables affect calling patterns and how local variation in call rates could be predicted, using the same variables, at these two distinctly different neighborhood sites. Given the complexity of the earlier spatial analyses, I focused my discussion on how the research did or did not support my hypotheses. I then discussed implications of these findings. I noted my important observations in Table 5 - Key Findings, below.

Table 5 - Key Findings

Key Findings

OLS - Local, Linear Statistical Model - Outputs	
Adjusted R^2 - Three Call Rate Models	The OLS regression model predicting rates for Physical Disorder Calls had the highest explanatory power: Adjusted R^2 = .0342, followed by Emergency Social Disorder Calls (0.324) and Social Disorder Calls (0.235). All models had very significant *F* statistics.
Predicting Call Rate Changes for the Three Models - OLS Global Coefficients for Independent Variables	
Variable Coefficients	The most influential variables predicting rate changes for '311 Physical Disorder Calls' were '311 Calls for Social Disorder' (0.754***), '911 Crime Calls Rate' (0.281***), and 'Percent Vacant Houses' (0.074***). The strongest coefficients predicting change in rates of '311 Social Disorder Calls' were rate of calls for 911 Crimes (0.151***), '311 Physical Disorder Call Rate' (0.130***), and 'Percent Foreign Born' (0.014***). While slightly less strong in confidence the following were the most influential variables predicting rate changes for '311 Emergency Social Disorder Calls': 'Rate of Calls 911 Crime' (2.780*), 'Physical Disorder Call Rate' (0.734**), and 'Social Disorder Call Rate' (0.114*) *p < .05; ** p < .01; *** p < .001 (two-tailed tests).
Other Observations on Variables	Where 'Percent Population Black' predicts increases in call rates for '311 Physical Disorder' (0.012***), and '311 Emergency Social Disorder' (0.003***) it predicts *decreases* in call rates for '311 Social Disorder' calls (-0.006***). 'Percent Foreign Born' predicts decreases in call rates for '311 Physical Disorder' and '311 Emergency Social Disorder' on call rates when it increases while the reverse was true for '311 Social Disorder Calls' where it predicts increases instead. Income, Education, and Population Density were particularly weak explanatory indicators of any rate changes, across all models, and held true for both statistical applications the OLS and GWR tests.
GWR - Local, Spatial Statistical Model - Outputs	
Adjusted R^2 - Three Call Rate Models	Adjusted R2 for predicting Physical Disorder Calls was substantially improved using the GWR model vs. the OLS (from 0.342 to 0.412).
	Adjusted R2 for prediction Social Disorder Calls decreased slightly from 0.235 to 0.200 with the GWR modeling.
	Adjusted R2 for prediction of Emergency Social Disorder Calls was reduced in explanatory power to and adjusted R2 of 0.272 (GWR) from 0.324 (OLS).
Better Model Fit/Specification	Lower AICc's (the regression diagnostic) are indicators of better model specification and those for the three GWR models were all substantially reduced compared to the earlier, OLS, AICc values.
Neighborhood Sites - Local R^2 Explanatory Power, Model to Model	The strongest explanatory power was found in Federal Hill cluster, predicting Physical Disorder Call rate changes (R2 = 0.61-0.71), while in Sandtown (0.41-0.50). Much stronger explanatory power for Social Disorder Calls in Sandtown (0.41-0.60) compared to Federal Hill (0.11 - 0.40), and explaining Emergency Social Disorder is roughly the same for both sites, about 0.31 - 0.50. Stronger explanation consistently appears in the south of Federal Hill for all three models.

Key Findings - Continued

Key Findings, Continued from previous page	
Neighborhoods Compared: Local Coefficient Variance Between Neighborhoods and Predicting Call Rate Changes for Each Model	
Predicting change in rates for *311 Physical Disorder Call Rates*	When predicting changes in rates for Physical Disorder calls model variables showed mixed enhancement and suppression in Sandtown, but, in Federal Hill, consistently suppressed rates. Only home ownership in Federal Hill is strongly associated with increased call rates. Notably this effect is much stronger than predicted in the OLS model. In Sandtown the strongest rate enhancers are 'Percent Vacant Houses' and increases in call rates of '311 Social Disorder' - a 1 unit increase predicts a 3 unit increase in call rates and this coefficient is *seven times* higher than Federal Hill's. Highly negative, rate supressing, coefficients include 'Income' in Sandtown, increases in rates of '311 Social Disorder Calls' in Federal Hill, and increases in rates of '311 Emergency Social Disorder Calls' at both sites. Notably '911 Crime Rate' is positive and fairly strong in its coefficient predicting increases in call rates in Sandtown about '311 Emergency Social Disorder' while strong in *suppressing* call rates about '311 Physical Disorder Calls'.
Predicting change in rates for *311 Social Disorder Calls*	Few of the model variables predicted '311 Social Disorder Calls' rate changes when looking at Sandtown-Winchester, save Education, which is strongly negative. However in Federal Hill the variables are mildly to strongly associated with increases in call rates. Of note is the very strong positive association found with an increase of 'Percent Foreign Born' and increases in calls for '311 Social Disorder' in Federal Hill. In Sandtown-Winchester however, this same variable acts as a suppressant to residents calling about Social Disorder issues.
Predicting change in rates for *311 Emergency Social Disorder Calls*	Explanatory coefficient values for this model had the widest range and thus strongest predictive measures. The variables here were positive and strongly predictive of increases in call rates in both neighborhoods, with even stronger coefficients in Sandtown than in Federal Hill. In Sandtown the strongest predictors were 'Percent Black', 'Median Income', and 'Crime Rate' (three times more impact than in Federal Hill), while 'Percent Families Living in Poverty' and '311 Physical Disorder Calls' were strongest in Federal Hill. The variable, 'Lived in Home Less Than 5 Years' was strongly suppressing of '311 Emergency Social Disorder Calls' rate in Sandtown - 30% less in fact - while in Federal Hill it *enhanced* the call rate. In Sandtown coefficients for '911 Crime Rate' and 'Percent Foreign Born' predicted increases for calls about 'Emergency Social Disorder' - and more than three and four times greater, respectively, than the effect found in Federal Hill for these same variables. Increases in coefficients for percent 'Homes Owned' and 'Vacant Houses' predict *decreases* in call rates for 'Emergency Social Disorder' calls in Federal Hill.

In summary, spatial analysts (1998) note that OLS models assume variables to be unrelated to one another in space. Observations are assumed to be stationary and independent of one another. However, using exploratory data analyses (ESDA), demonstrated with the LISA measures maps, and spatial analyses such as GWR tests, the researcher can adjust for the non-stationarity and demonstrate that variable values *are* influenced by other nearby values, and so violate the cardinal assumptions underlying OLS regressions when they are not independent.

Comparing methodologies OLS predictive outputs exhibited a more conservative predictive and explanatory power than GWR when used with these variables in Model One, predicting changes in call rates for 311 Physical Disorder. In the other two models, the GWR measures were more conservative in explanatory power than the OLS. These differences highlight how, in some cases, GWR avoids glossing over differences in local spaces and may reveal a more accurate picture of how variables relate and influence one another, even if that means a decrease in predictive power.

Uncovering Local Variation in Coefficient Strengths Using GWR

A major strength of GWR is its ability to illustrate and illuminate the sometimes hidden differences at the local, or even micro, level for individual model variables and their locally shifting values--spatial shifts that may otherwise be subsumed in aggregated data when using linear/global OLS models.

Comparing these two very, indeed diametrically, different neighborhood sites across all three call-rate model types, we discover substantial differences in the strengths of each of the predictor variables and their calculated contributions to explanations of call-rate changes, depending on the statistical method as well as the call rate prediction.[14] In some cases, this meant changes in not only the strength of the predictive variable but also its *direction* of the parameter estimate, swinging from enhancing to suppressing call rates when moving from one model to the next.

In otherwise aggregate-determined models (OLS), any maps produced would display uniform color across, say, a census block, having followed the assumption of data independence across that space. In GWR generated maps, however, there is clear spatial variation in the predictive strength of parameter estimates mapped across a neighborhood. The GIS (software) demonstrates this using color and a cold-to-hot temperature theme, where the lowest predictive strength (which may be negative *or* positive in directional impact we must keep in mind) is colored blue (R2 < 0.11), moderate power to predict changes in rates is colored yellow (R2 0.41 to 0.60), and so on, through orange and red values, up to R2 values of 0.70 to 0.90 and higher. The GWR maps created for this project use the same color metric for each variable, and in every call rate change prediction model, to demonstrate the *relative* strength of each variable within a neighborhood -- not just the magnitude of its impact on call rates. I refer the reader to the appendix for separate maps that include the range of coefficient values measured for each locale, as well as a summary chart denoting variations in parameter estimate values from model to model and by methodology.

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[14] Because of the calculus used to construct GWR results, GWR does not produce *p*-values. In a GWR, *p*-values cannot truly represent significance because they do not include the global *weighting* of a parameter's local value. That is, *p*-values are globally determined and dependent, while GWR values are local.

IMPLICATIONS

Social Disorganization, Space, and People

Kubrin and Weitzer begin their review of the state of social disorganization theory by pointing out that, while some theories focus on "kinds of people" when explaining crime, social disorganization theory focuses on "kinds of places." To that end specifically, the focus here is on kinds of neighborhoods (Kubrin and Weitzer 2003, p374). So how might *place* explain the results found in this research?

What about Geography?

Comparing the Sandtown-Winchester neighborhood with Federal Hill reveals a stark, night-and-day difference, one captured in the following photo (see Figure 28). While Federal Hill has its share of problems and is hardly devoid of crime, the general sense of it, how it is known in common parlance, in and outside of the city, is that it is a space that is largely rich, resourced, vibrant, and gentrified. It is moving forward.

By contrast, the world that is Sandtown-Winchester, is, at best, bleak. The photo, taken in February of 2011, but could be any day, any year in the past ten years and the recent three going forward, shows neighbors in front of a few of the hundreds of vacant houses in their environs; they were waiting while police cleared yet another murder scene in their neighborhood. An average of 21 people were murdered in the 21217 zip code, from 2008-2011 (Fenton 2012) and that number has not declined since.

Figure 28. Waiting in Sandtown-Winchester. Photo credit: Justin Fenton, Baltimore Sun, February 2011

How space like this came about is no accident. William Julius Wilson showed how concentrations of African Americans had come to dominate certain urban spaces after the decline of manufacturing and the departure of the African American working and middle classes to more suburban areas. Wilson related how these changes in economic prospects for the remaining men left them less marry-able, fostered an increase in households headed by single women, and generally increased poverty. African Americans, already disadvantaged by systemic racism, suffered disproportionately from these structural changes in the larger society (Massey and Denton 1993, Wilson 1987). A confluence of social structural events led to what Massey and Denton called hypersegregation--geographic spaces in which populations of Blacks found themselves isolated, segregated, and concentrated in poverty and social disenfranchisement (Massey and Denton 1993). This phenomenon is evident in the 97% Black population of Sandtown-Winchester, in the persistently lower rates of employment and high-school graduation, and in the quintupled poverty rate of families living here as compared to Federal Hill.

These concentration effects go further still. Locally, they breed prevalent feelings of despair, hopelessness, and pessimism (Wilson 1996). Jock Young states that residents in spaces such as Sandtown-Winchester have become so isolated and so lacking in stable social and cultural organizations that they have become an urban underclass without *culture* (Young 1999). Described in this manner, they are a group so removed from the social mainstream, so economically and morally bankrupt, that they no longer have anyone upon whom they can draw to help them build a different vision of their own neighborhood space. Instead they are relegated to the inevitable--the constant decline of their neighborhood, with no hope of changing it or escaping--and so, they are left to "wait." And to be clear, "moral bankruptcy" isn't meant to be disparaging. Yes, many persons become "successful" in difficult situations, and under enormous restraints. However, the situation Young is painting is *beyond* hope and utterly lacking in the support that would aid them because those external to that neighborhood have given up on them – not the other way around. Every day in these spaces people get up, go to work, raise children, love, live and die. However, they clearly are not moving *forward* either and they do not remain in that neighborhood *by choice*.

The three neighborhoods of Sandtown-Winchester, Upton, and Druid Heights, are, by all traditional measures, the more disorganized of the two studied sites: they have more physical decay, trash, and physical infrastructure problems, as well as multiple social ills and challenges. Yet, an examination of their calling-rate patterns simply does not support the theory that these neighborhoods have given up on trying to improve their space. Instead, we see an "organized slum" with residents who *appear* to be disorganized, who are, in fact, socially and civically engaged (see Sánchez-Jankowski 2008). However, there do remain the larger issues of what constitutes *effective* action and at *whose vision* for that neighborhood it is directed.

Neighborhood Change Capacity

William Julius Wilson noted that the only way out of the hypersegregation Blacks faced was for them to become more culturally and economically integrated. However, looking normatively at the current maps of responses, by the strengths of different predictor variables of call rates, the two neighborhoods could not now be further apart. The oppositional shifts, from site to site, from model to model, are not clear in their genesis, but the sheer *volume* of calls being made in Sandtown-Winchester, as compared to Federal Hill, appears indicative of larger, more institutional issues and a lack of response to this neighborhood's cries for help. Sandtown-Winchester residents place *thirty-one times more narcotics-related calls* to the police than the city average call rate. In contrast, Federal Hill's drug-related call rate is roughly double the citywide average. So does Sandtown-Winchester really harbor thirty-one times more drug dealers and users than the city average? Perhaps. But other indicators in this research suggest that actually the police and municipal officials don't respond to these issues with the same impetus to quell them as in other neighborhoods. Regardless it still wouldn't explain why, in such a disorganized space, residents would still care enough, be galvanized enough, be even trying to address this problem.

My interpretation is not that Sandtown-Winchester simply lacks the capacity to solve its problems. Rather, there is probably also an institutional disconnect: a lack of commitment to work with these communities to resolve their problems on the part of the formal control systems and institutions – those groups charged and responsible for the necessary changes that would resolve these issues. People like code enforcement handing out citations, and police effectively arresting area drug dealers. Instead, this neighborhood might be further marginalized by opportunistic policing, something that erodes community trust, not only trust in the police, but *also* among the residents as police leverage and use residents one against each other, for example often bargaining with "snitches" for information (Natapoff 2004).

At the same time, the types of calls getting attention differ in the two studied neighborhood sites. In Sandtown-Winchester, enormous volumes of calls are made about larger and more urgent issues. The sheer volume of calls to these issues has to crowd out the residents' time to work on, or address, more locally-beneficial and forward-looking issues. In, for instance, the photo above, the omnipresence of "the vacant" is the signature component of neighborhood life in Sandtown-Winchester. They stand guard in an almost perverse way while mocking the residents' daily. They demand attention and energies constantly – prevent someone from setting fire to them, or prevent someone else from using them as disposal sites for murder victims' bodies. Such dreadful possibilities seem extreme but were dramatize real-life and major plot lines used in the popular HBO series, *The Wire*, the drama based on life in Baltimore's toughest neighborhoods.

How can these neighborhoods move their spaces forward? That is a practical question that addresses the utility of this kind of research. Sampson et al. (Sampson, Raudenbush and Earls 1998) pointed out that more is required than merely correcting a neighborhood's physical and social disorder. That is supported by the OLS and GWR regression outputs that indicated that, while neighborhood disorder predicts increases in calls about remediating Physical Disorder, it is not clear that such disorder call participation will fuel action to solve *social* disorder next. Instead, Sampson and Sánchez-Jankowski said that we need to employ a combination of neighborhood characteristics and social ties theory to account for both crime and disorder there. The social ties -- people's interelations with one another, close and personal to far and distant -- are key. They act as the gateway to enhancing two kinds of participation: instrumental and expressive, where instrumental actors focus on what an action does to further a goal or issue resolution whereas expressive participation is centered in doing because it feels right and affirms group identity (Swaroop and Morenoff (2006)).

Swaroop and Morenoff (2006) noted that a neighborhood's residents' capacity to participate instrumentally, that is participate in groups dedicated to improving a neighborhood's condition, has been found to be positively associated with socioeconomic disadvantage. However, no association has been found between these same kinds of poor neighborhoods and an ability to participate within them in an *expressive* participation manner. This lack is important because expressive participation is required in the formal organizations that promote neighborhood solidarity and a sense of community. And, as Mead points out, expressive participation has become a universalized sense of the community's *generalized other*; to have proper effect in a community it is dependent on the degree to which a generalized other can *become* universalized, that it becomes understood, expected and internalized by all community members (Mead and Morris 1967, p266). Less privileged neighborhoods are at a disadvantage then. Their members are unable, or often lack the sufficient skills, time, and tools to participate in formal organization and institutional capacity building; hence they have less opportunity to augment their informal sanctions with *formal ones* that would otherwise help sustain their community while adding to a more complex tool box of solutions. Without expressive participation then they will continue to lack the local social cohesion required to maximize their energies and actions; no matter how many problems they are facing they will never move beyond crisis control without the requisite tools to compete in the larger political forums that are responsible partners in solving their problems.

Resident Engagement and Competing Visions of "Neighborhood"

Competing interests (visions of what is or will be considered to be acceptable levels of social and physical incivilities) certainly undermine the ability of *any* community to move forward. Kubrin and Weitzer (2003) note that informal social controls can either help *or hinder* social organization. A neighborhood has more than just law-abiding citizens who use mechanisms (such as 311 and 911 telephone calls) to effect change there. Some people use informal social control against "bad behaviors" while others, such as criminals, might use these tools to *conserve* the status quo (Sánchez-Jankowski 2008), even undermining those trying to make "positive" changes happen. As above, while some might want social and physical change to happen the tools of change can be used in these dispossessed neighborhoods *against* positive change.

In *Cracks in the Pavement: Social Change and Resilience in Poor Neighborhoods,* Sánchez-Jankowski explains how change agents work, not only within a neighborhood, to maintain the status quo, but to shape and maintain social order (Sánchez-Jankowski 2008). While I have talked mostly about how Sandtown-Winchester is disorderly, yet functionally so, we must also consider that Federal Hill polices the boundaries of what is "acceptable" by its residents as those residents too try to maintain "the status quo" for their place.

In this regard, of all the findings generated from this project, two stand out the most. First, residents in Federal Hill called more about "suspicious people" than did the residents of Sandtown-Winchester. Yet, in the latter neighborhood, crime rates are 10 to 15 times higher than in Federal Hill. Second, the measure of "Percent Foreign Born" was differently predictive in the two neighborhood spaces. In each case, it appears that "the outsider" coming into a neighborhood space provokes a particular kind of response. In Federal Hill, as the percent of the population reported to be Foreign Born increased, we could predict commensurate increases in calls made about social disorder in that neighborhood. Yet, the same increases in "Foreign Born" in Sandtown-Winchester appeared to increase social disorganization there, although call rates actually went *down*. Could changes in local neighborhood composition fuel alternate outcomes, and if so, why?

However, other sociologists note that the most tenuous connection to make is the development of social norms from the local into some larger, aggregated understanding of what is right and what is wrong. In addition, if we are to accept (and I believe it's reasonable to do so) that neighborhoods share some kind of *generalized other* vision of how they think of themselves and of how others think of them, then there must be some mechanism in operation for that cultural transference. Cherkaoui (2005), exploring James Coleman's discussions on Rational Choice Theory noted that "the maximum utility principle" for individual actions is not enough to explain why people act the way they do. And the same applies when looking at neighborhoods in action. So why, if a neighborhood is as fractured by social and physical disorganization as Sandtown-Winchester is shown to be here, are the residents able to exercise some kind of normative neighborhood *generalized other* there? Is the emergence and fostering of such a norm happening in these "significant clusters" we see when crime is rife and people call?

Cherkaoui noted that norm production can follow from two major mechanisms: imposed by an institutional apparatus, such as police or courts, or "through the *aggregation* of individual behaviors." I emphasize the aggregate part because so many planners and community developers note that that component is necessary to the ideal neighborhood. Yet, without it, we are unlikely to see development in a direction away from poverty, fear, and crime, in places like Sandtown-Winchester, especially when the institutional mechanisms (legal, economic, social, racialized structures like courts and corrections, etc.) do not operate equally on their behalf. Without aggregation, this and other neighborhoods like it are doomed to flounder in a sea of incivilities, never joining together for mutual survival and never even knowing if they are making headway against that tide that is most certainly drowning them.

Therefore, one role of spatial sociology here could be to help identify clusters in neighborhoods--seeds of normative change—to not just the municipal agents but to the neighborhoods themselves. Those residents believing they were morally bankrupt (because that's what outsiders are telling them) could be nurtured, helped to develop solidarity against the onslaught and the political tools to engage in the forums that resolve more than spatial issues. And we could use our measurement tools more proactively, identifying and inferring which communities are already at risk before it's too late. We know and speak about them as "at risk" every day. Instead, why not help them develop the mechanisms to nurture civic capacity, to instill their own norms throughout a neighborhood, rather than describing to them what they already know, or imposing social expectations? What such a nurtured neighborhood would look like, or that resident as an "engaged" and "civically responsible" individual is not clear, but it is a step in the right direction no doubt.

The Ideal Neighborhood and the Ideal Resident

In his book, *Common Places,* David Hummon articulates how idealized visions of the proper modern city dweller have evolved into the "New Urban Pioneer" (Hummon 1990). This new urban pioneer is enthusiastic about the challenges of living in "transitional neighborhoods," for example. However, the term "transitional" is vague. Transitioning to *What*? And *Who* says when that voyage is underway, what shall be the path, and when one has arrived or the journey is complete? Like the earlier conversation here about Formstone and social class in Baltimore, the transition is supposed to be in one direction: toward gentrification. Gentrification usually brings with it transitions to a new way of life, a life that fits the new, encroaching, urban pioneers' social and behavioral expectations, what *they* feel that neighborhood should resemble and how it should *act*, no matter how romantic or misguided those expectations may be. If that transition is to be successful, it demands a degree of surveillance and imposition of ideals on the *existing* residents, persons unwilling or often unable to move away.

We see such modification and integration problems precisely in Federal Hill and SOBO (South Baltimore), located on the southern border of the Federal Hill neighborhoods group studied here. In SOBO today, White working class residents are clinging to their culture in spite of the onslaught of newcomers. The once ubiquitous Baltimore corner stores, where these neighbors can congregate and drink cheap "Natty Boh" beer are being pushed out, identified as disreputable, and not in keeping with the future image the new neighborhood wants to put forth. Packaged goods stores are replaced instead with bistros and wine shops. Whether or not those experiencing the incursion of "New Urban Pioneers" will stay is largely a matter of sacrifice, as Jessie Bernard said (Bernard 1973). That sacrifice goes hand in hand with a commitment to participate in a community, to forge with other members bonds that can stand up against outer *and inner* threats to the group's existence. It is not enough to *be* in a neighborhood; such pioneers have to commit to, and participate in, the creation of social structures that will serve and *defend* the ideal of community that supports its own continuity.

If newcomers are not willing to do so, they will find themselves cast out, pushed aside, priced out, bulldozed, etc. There are plenty of examples in Baltimore where the less powerful are uprooted without ceremony or apology in the name of progress. From the $1 homes noted in the introductory review here to the more recent failed development of the Middle East affordable housing projects by Johns Hopkins University where over 800 homes were bulldozed to make room for Johns Hopkins expansion and then the homes largely never materialized the story is basically the same: Put up, shut up, or move out and on. Even in the dominantly white, hipster-frequented corridor of North Avenue where MICA (Maryland Institute College of Art) students roam, the constant press and scrutiny of developers ready to exploit the newly transitioning area is palpable. And while the hipsters are ready to defend this turf they are clearly on the "wrong side" of the "ideal community" when they promote groups like "Gentrification (k)NOT" in response to these economic shifts(Brown).

This commitment is the kind of thing that moves people from being isolated, Gesellschaft-type, community members, to "urban villagers," to becoming those engaged pioneers of Baltimore's earlier "$1 Homes." This is not to say the $1 Homes were a *success for everyone* – but they were for those privileged enough to get one.

The “successful community” is currently one that has connected, and cohesively supportive residents who are best equipped to respond to challenges and problems they might face in their neighborhood--problems those living in “concentrated disadvantage” simply cannot tackle in their current state of disenfranchisement, displacement, or disarray.

In his text, *The Good Neighborhood,* urban planner Sydney Brower goes to lengths to develop typologies of neighborhoods across multiple planes: rural vs. urban, old vs. new, real vs. the mythical and ideal form of a neighborhood. While researching, he noted inconsistencies in what residents would use as metrics to measure that “good neighborhood.” He compiled multiple case studies to determine what would be a universally agreed-upon type of space that would be considered a “satisfactory neighborhood,” a space that residents would describe as a “good place to live.” Brower then described that space using his own important quality-neighborhood dimensions: Ambience, Engagement, and Choicefulness.

Ambience, he explained, for an urban space, means houses close to one another, with a definite center of activity; it is entirely residential and is, among other qualities, a place “full of surprises.” He notes that the primary quality of a neighborhood with ambience is its *physical maintenance quality:* it is well kept and “absent of disorder” (Brower 1996, 97, my emphasis). Along with buildings and sidewalks in good repair and a lack of trash, is a sense of tranquility that emerges in the studies he reviewed. Such a space is “*a place where people feel safe and secure,*” a place for newcomers and tourists, where people know one another. Finally, a neighborhood with choicefulness is a place with a “good reputation, the place you’d like to raise a child, and a place of diversity, among other things. (Brower 1996, 94-107, my emphasis where noted).

Now let us look back at our two neighborhoods-- the poor and disenfranchised living among vacant burned-out shells and echoes of gunfire in Sandtown-Winchester, and the well-heeled and educated, at the Ritz-Carlton condominiums with their nearby boat slips at Federal Hill. Whose neighborhood would be considered “satisfactory”? This study was drawn purposefully from two extremes to make the point that such neighborhoods do in fact exist. And while Brower and Hummon talk about ideal neighborhoods and the beauty in the more random nature of city life, that doesn’t change the fact that Sandtown-Winchester is not a neighborhood of “choicefulness” - not on the best of days. Brower doesn’t hide this issue, but he doesn’t necessarily address it either.

Urban planners like Brower are trying to describe and theorize, even build, the elusive *ideal* space in which to live and work. However, so much of this theoretical idealism continues to leave the “not good” neighborhood out of the equation. The Baltimore Inner Harbor plan and the $1 Homes program whose legacies reverberate decades later represented waves of White wealth but still remains to share that wealth with their neighbors on whose backs, arguably, it was built. And we continue to engage in this dialogue about a mythical hunt for the ideal neighborhood rather than discussing how we can get residents “up” and “engaged.” Indeed, Brower noted that “people will not engage with one another in a climate of fear” (Brower 1996, 100), so one wonders when Sandtown-Winchester will have its monstrous crime rates brought under control, and conspiratorially speaking it makes one wonder if anyone *wants* that to happen. Yet, these residents are fighting against crime and for a better future. This research makes that clear. But they aren't going to make it all alone.

Beyond Neighborhood "Disorder" As A Predictor of Behavior – Attending to Cultural Aspects of the Neighborhood

Elijah Anderson is well known for his meticulous and insightful ethnographies of inner city Philadelphia. His observations are particularly illuminating here, in Baltimore, where citizens, particularly impoverished African Americans, are burdened with negative perceptions--the stigma, or even guilt by association, of where they live now, once lived, or grew up. Neighborhood names such as Cherry Hill or East Lanvale, or streets such as Kennedy, Bentalou, or Park Heights conjure immediate images of "the ghetto." In contrast reflections on Federal Hill, Fells Point, or Roland Park create much opposite visions. Those visions of neighborhood of course map onto the identities of the persons who resident there as well. Both internally by residents and externally by visitors, and sometimes onlookers or even voyeurs one might say, in the case of *The Wire*.

African American men, for example, might be racialized and marginalized, but through those processes are still able to *choose* to be in opposition to the dominant White culture. We see this expressed regularly in fashion, language, or cultural norms (Anderson 1999). Anderson noted, too, that this antagonistic stance maps back onto the community and its inhabitants. Consider not only the characters of David Simon's *The Wire* (Chapelle 2002-2008) who were always on the wrong side of anything lucky, but how Simon cast the *neighborhood* as a character itself--something that the characters could not escape from. And in Simon's earlier work, *The Corner* (Dutton

2000), he forged this connection even more clearly, not just metaphorically but by the title of the mini-series itself. *The Corner* displayed the hold that geography has over many Baltimoreans and their lives while the residents oozed despair, and as "Gary" and "Francine" tried to escape it and the drug dealers that dominated every aspect of people's lives there. Even more brutal was how art and life imitated each other when, in August 2012, DeAndre McCullough, who played *himself*, in *The Corner*, the drug-dealing son of Gary and Francine, was found dead of an apparent heroin overdose in West Baltimore and an "all too familiar fate" (Swarns 2012). In this way Place, and Baltimore is not all that different than other such deindustrialized cities, symbolically and literally has become inescapable; it follows, to some degree, akin to Wilson's (1987) "concentration" effects then that "the there" one inhabits actually begins to inhabit *you*. It has become a kind of self-fulfilling, existential prophecy: to live in a certain place is to *be* that place and choice and agency are removed from the day to day matrix.

Panelli says that actions are the ways we explore our personal sense of self and our identities, and that we do this in spaces and neighborhoods (Panelli 2004). But important, and highly problematic is that "…where social action involves the collective mobilization of different power relations and activities, then the performance of these actions will both take up and constitute/reconstitute space" (Rose, in Panelli 2004, p197). The construction of one's self is *not* independent of the space one inhabits, and like DeAndre, above, there are "different power relations and activities" acting on us and shaping what and who we can be, what we can *do* in those spaces. As Anderson notes above, the ghetto reads onto people, and vice versa. In background of the ghetto the meanings, the powerful repercussions of race, class, locality, geography, and meaning are continually reinforced, a position underlined by Wilson's work (1987). A recent *Baltimore Examiner* news article illustrates this case too well, recounting how then Mayor-to-be, Stephanie Rawlings-Blake, was on a citizen's patrol/photo op in Baltimore.

> "Just what area was Rawlings-Blake & Co. patrolling (with 30 cops with her)? The Block *[the notorious sex club strip downtown]*? West Baltimore? *[where DeAndre McCullough, above, died]?* Settings *[sic]* from *The Wire*? Nope. None of the above. The next Mayor was patrolling one of the safest and most aesthetically pleasing neighborhoods in the city: Federal Hill…the neighborhood is mostly safe, <u>especially when compared to other areas of the city</u>" (O'Donnell 2010, emphasis added)

Every day, the privileged and well-heeled neighborhoods are built-up, supported, and doubly enhanced by words, comments, and the entrenched meanings supported by powerful persons and institutions that stand to benefit from their continued good standing. Other neighborhoods, however, are demeaned and vilified, along with those who live in them. Yet these same residents are striving, just like those persons in Federal Hill, for better lives and neighborhoods. My research has shown how individuals, and those specifically living in stigmatized and disenfranchised locales are working hard to effect positive change. Yet, repeatedly, these residents find themselves marginalized before they can get positive change underway--all because where they live supposedly says more about *them* than the space itself.

Hayward and Belfoure recounted in *Baltimore Rowhouse* how, during the demolition of the notorious Lafayette Court public housing high-rises in Baltimore, those being moved asked to be re-housed in "rowhouses… We just want to live in the same kind of housing that everyone else has" (Hayward and Belfoure 2001, p187). They also point out how the rowhouse is one of the perfect vehicles of community integration--

doors that all open out to one another so people can look out for their neighbors. While that neglects the obvious problems of marginalization, the research results here show that physical environment -- and the two study sites are dominated by this kind of rowhouse environment -- when it is physically decayed, does have a significant effect on some kinds of community engagement. Independent of the architecture itself then all the rowhouses in the world won't benefit the poor or dispossessed, nor will that housing form assist them in developing a more actively engaged community unless we develop a deep understanding of the local, and often competing, cultural ideologies at work, both between, and within, neighborhoods.

Limitations

Several issues require future attention to render the results more robust. They include the following:

1) There is a need to develop a more comprehensive model of predicting resident behavior that includes measures of cultural difference and community investment.
2) Such models should test for not only the informal social controls used here but also formal ones. Too often, models predicting neighborhood social change include only one aspect of that change, usually the informal controls (Kubrin and Weitzer 2003).
3) The research outcomes are limited to these local sites *only* because of the specificity of the data being addressed and local itself. However, the protocol of analyses should be useful at other urban sites. Yet, one should be aware that scaling the size of any respective spaces being studied can change the meanings and interpretations.

4) Social ties and local associations were not included in the analysis, so the role of cultural differences and social connections cannot be extracted or discounted properly.

Closing

Forces of change, whether conflictual or consensual, are the mechanisms that keep a neighborhood moving (Sánchez-Jankowski 2008); either in growth or decline, it is always in a state of flux. Sánchez-Jankowski stated "The persistently poor neighborhood is a composite of activities producing a social equilibrium that forms the basis of a *functionally reproducing neighborhood"* (Sánchez-Jankowski 2008, p51, emphasis added). Some might argue that such neighborhoods aren't interested in engaging, that the poor and dispossessed and don't identify with their communities because they have experienced social and institutional segregation. They stated further that "these people" would not be able to combat the ills around them because, with so much disorder, they would be unlikely to nurture the social ties that would help create a coordinated response against problems; apathy, instead, would set in (Warren 1971).

Persistent poverty is not a beneficial state for any community. This research project has explored how a persistently poor, disadvantaged neighborhood compares to a similarly built and sized neighborhood, but one with much more economic and social capital to draw upon. This study has sought to determine what, if any, role disorganization might have played in the differences within and between those communities as they sought to change their own spaces. It found that differences were apparent in community engagement, but not necessarily as expected. The built environment alone, while a strong predictor of levels of resident engagement, could not be taken as a given, out of community and social context, the spaces in which those variables operated, if its role in shaping neighborhood action was to be better understood. Poor neighborhoods did, in fact, have higher engagement rates, even when more socially and physically disordered than their richer neighbors. However, it is not clear whether or not these two spaces were treated equally or meaningfully, by institutions or outsiders, and especially those *charged with assisting change* agents in the first place. And then when stigma, racism, and social structural mechanisms collide with local micro-cultural meanings, situated in these spaces, the ultimate synthesis may be a community that, while disordered, on the surface *looks* like it's active and engaged. But the question remains to learn whether or not these communities are acting on their own, chosen, culturally-specific paths, or are they under siege, fighting for survival and able to create a community that sees itself as one – a powerful and purposeful *generalized other* with a future it will write through the actions of its residents rather than being written about and defined by outsiders.

APPENDICES

APPENDIX I – METHODS

Data Transformations

Data Transformation Methods for Point to Raster, Raster to Point, Point to Krige

In order to transform locally addressed point values to raster surfaces then to gridded centroids for kriging and the creation of each variable's event/observation surfaces the following steps were taken using ArcView software to transform the data into those event/observation surfaces:

1. **Geo-code Observations** – Calls for service, with addresses, were geo-coded – located in space – and placed on a map layer – a spatial representation locating all calls relative to one another in space.

2. **Point to Raster Transformation (ArcToolbox)** - Geo-coded point shape file used that denoted <u>location</u> of observed, known, calls made. I chose a cell size (250 x 250 sq. ft.) for the output raster (continuous value surface.) The cell size determined the number of observed calls "captured" in that cell. Using ArcView I selected the [SUM] function and the conversion used the raster cell boundaries to sum the number of point features (calls made, in this case) within its bounds. The output raster includes an ATTIBUTE TABLE where the values found under the GRID CODE heading is the <u>count</u> of calls made within that cell. There were cells where no values existed, which was fine. The next step converts raster grid values *back to a point* shapefile layer in

preparation for interpolation of the missing values using kriging, filling in those unobserved values.

3. **Raster to Point Transformation** – This step converts the raster grid values into a point feature layer, and in doing so importantly creates call counts, as part of that point's attributes (as an aggregate of separately addressed points located within that cell, since assigned to that cell in the raster conversion earlier) . Select "GRID CODE" in the attribute table of the outputted point feature and assign this to the point as its value. Next, interpolate for missing values.

4. **Point to Krige Transformation** – This step interpolates what would be the *likely* call volumes in the interstitial "white spaces" between *known* values. The key difference methodologically here is that they are centered now based on the previous raster grid cell structure, rather than using some artificial centroid found within an administrative or political boundary polygon – the method most commonly used to aggregate data to points in areal space. The output then is a continuous or smoothed surface of values, taken every 250', across the entire spatial plane of the city - an isopleth map containing *expected* calls where there were none before.

APPENDIX II – RESULTS

Maps Indicating Spatial Distribution of Dependent Variables

Note: Sandtown cluster is located to the north, Federal Hill cluster to the south

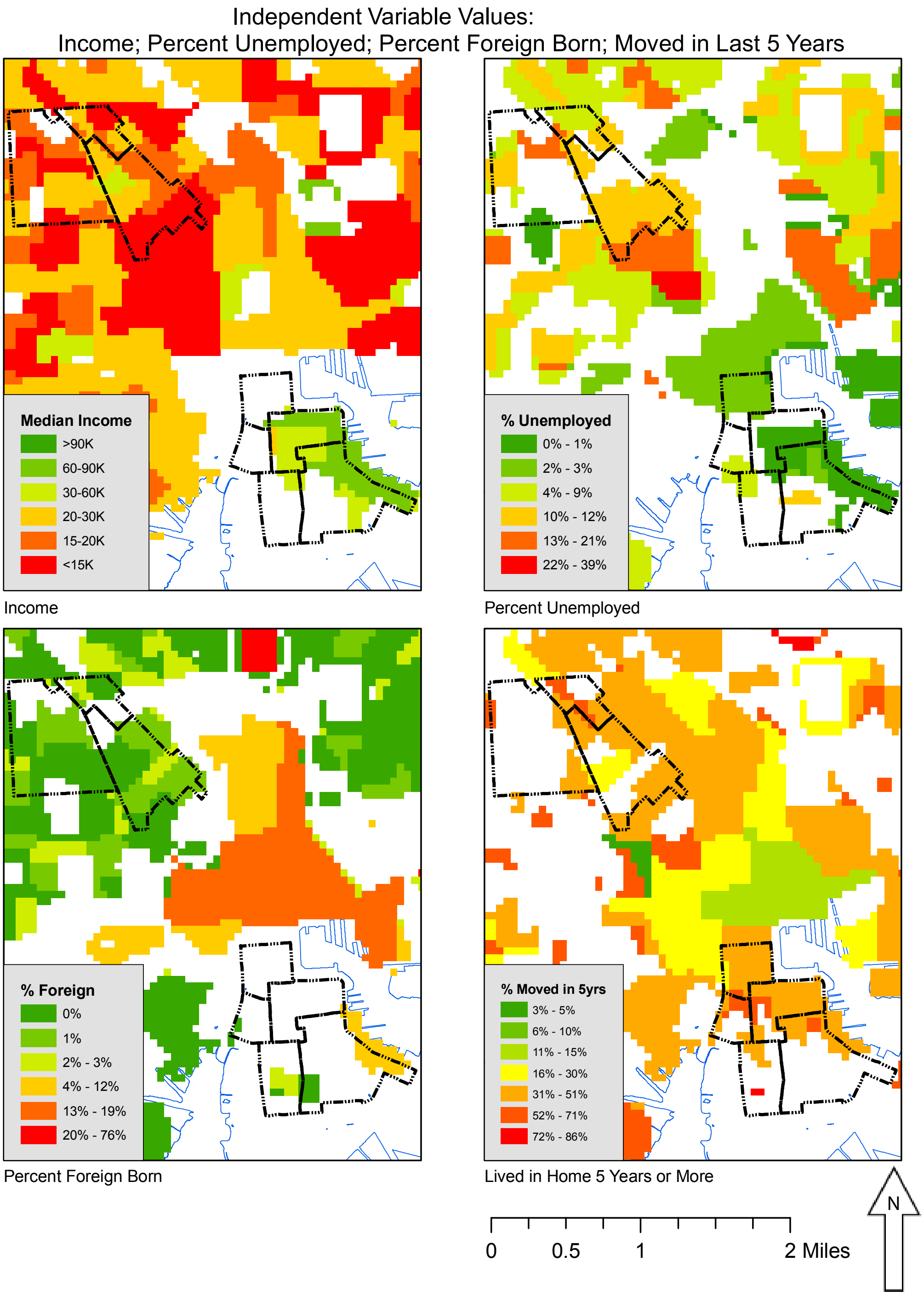

Figure 29 - Independent variable values – local spatial distribution and concentrations: Median household income, percent of residents unemployed, percent of residents foreign-born, percent of those who had moved within the last five years.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

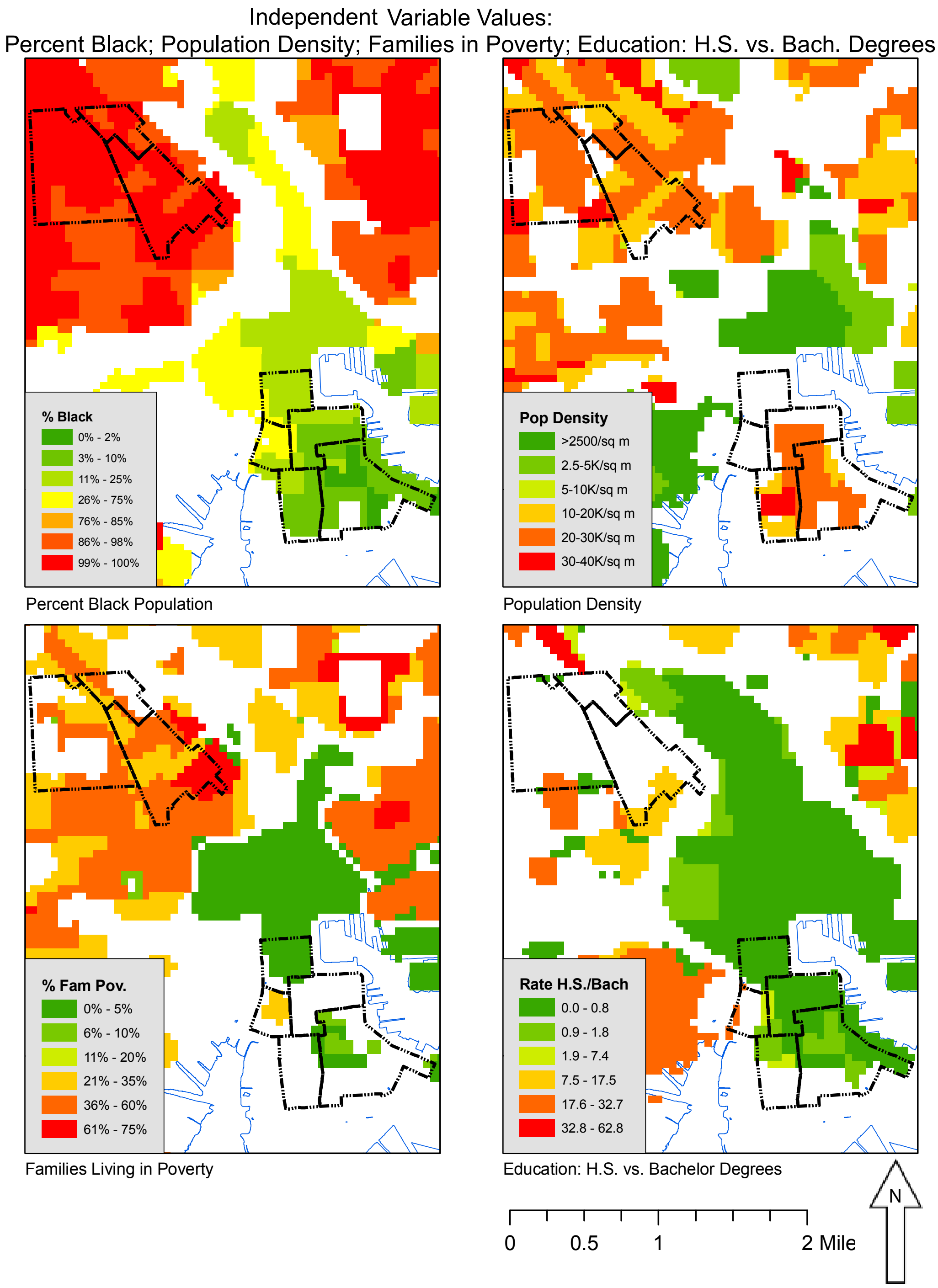

Figure 30 - Independent variable values – local spatial distribution and concentrations: Percent residents Black, Population Density (per square mile), Percent of families living in poverty, Ratio of residents holding high school versus bachelor diploma/degrees

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

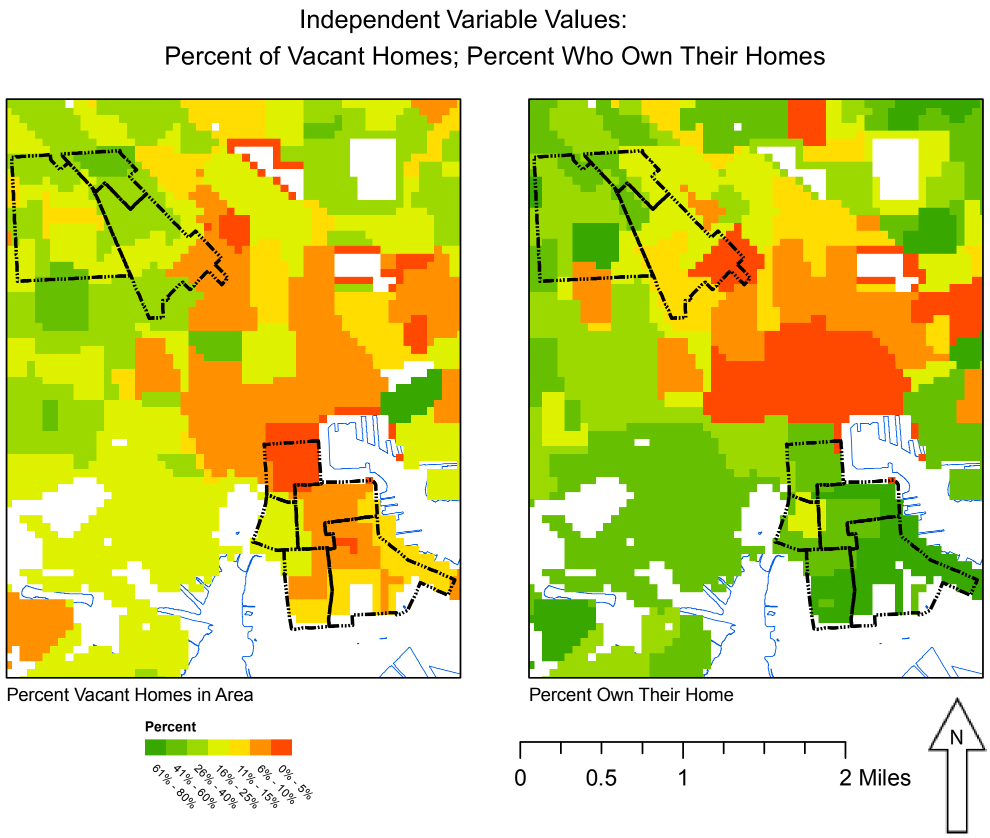

Figure 31 - Independent variable values – local spatial distribution and concentrations: Percent of neighborhood homes vacant (where darker green indicates higher concentrations of vacant homes, red less) and Percent of residents who owned their own homes. Darker green indicating higher values of ownership -- versus higher indicators of rentals, indicated with yellow through reds.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

Detailed OLS and GWR Results Discussion

This section provides detailed discussion for the interested reader on how OLS and GWR results were determined and specific outcomes and measures for all independent and dependent variables across the three predictive call rate models. OLS and GWR model results are reported, respectively to demonstrate how spatially weighted variables can alter the weight particular variables contribute to predictive model outcomes and thus their coefficients of prediction.

I first report the OLS, or "global model" results using the three, different, call rate types to see how the independent variables and other call rates predict each. This is a global method because it takes the *entirety* of the data set as its beginning and end, irrespective of the spatial location of any variable and its values. Next I present the GWR, the geographically weighted, or local model, and its outputs for each of the call rate types and their respective variable coefficients. This modeling is local; at any given location across the breadth of the space analyzed, separate, "local", predictive equations are generated for each of the three call-rate models. I also explore overall differences between the predictive strengths of the local and global models, as well as review how the models differ for the call rate types and how, within each of the global and local models' the variables themselves exhibit power and direction differences for their respective coefficients.

OLS Model Results.

Multiple regression analyses were performed on three separate call rate predicting models using the above-mentioned parameters. The first model predicted the rate of calls, per 1000 persons, for neighborhood physical disorder issues. These residents called about physical deterioration of their lived in spaces – from collapsed buildings, grass at a neighbor's that was overgrown, a street pothole in need of repair, a street light burned out, to animals running at large or annoying rodents and pests – in an attempt to have those problems resolved. The model then seeks to predict how social disorganization variables augment or suppressed calling behavior in the two neighborhoods of interest. All call rates were derived from a three-year period from 2006 to 2009 while demographic variables were extracted and calculated from 2000 Census data (see .Table 1)

Outputs of OLS Global Statistical Modeling Predicting Call Rate Changes

The OLS global statistic method analyses demonstrated that all variables included in the models were statistically significant predicting rate change in all three different models. The OLS results indicated the model best explained by the social and physical disorder variables was calls concerning "311 Physical Disorder", adjusted R2 = 0.34, slightly less power predicting "311 Emergency Social Disorder Calls" rate changes (R2 =0.32) and the least explanatory power when considering their effect on "311 Social Disorder" call rates, with an R2 = 0.24.

OLS Models Predicting Calling Rates for the Three Call Rate Types

Predicting 311 Call Rates for Physical Disorder Issues Using the OLS Global Model.

When used to predict the rate of 311 Calls for Physical Disorder the OLS regression produced an adjusted R2 = 0.342, and F (14, 25804) = 1033.59, p <.0001. The results (see Table 6) indicate that all predictor variables were all statistically significant predicting call change. with p <.001, save the education variable which was significant only to a p<.01. The variables for "Median Income", "Population Density", and Education (high school vs. bachelor degrees) provide little explanatory power of the overall model. The strongest predictor for changes in calls about Physical Disorder in this model was “Rate of Calls for Social Disorder”. A positive and significant regression coefficient value of 0.754 indicates for every measured increase in the rate of calls for social disorder we can expect a 0.75 increase in the rate of calls made about physical disorder. “Rate of Calls 911 Crimes” also significantly contributed to positive correlations in physical disorder calls - a reported coefficient of 0.281 – or for every three fold increase in crime rate calls results we would see in a increase of ‘1’ in the rate of calls made about physical disorder. Increased concentration of unemployed persons, and the proportion of African Americans in a neighborhood also indicate very slight increases in calling rates. Not surprising perhaps is that the rate of calls made for physical disorder issues increases in the presence of increased numbers of vacant homes, with a positive coefficient of 0.074. But, somewhat counterintuitive perhaps, whether or not residents own their home contributes significantly less to explaining rate variance for call rates about physical disorder (0.019) than the presence of vacant homes themselves; homeownership itself does not seem to contribute to a social control mechanisms that enhance informal policing about physical disorder issues so much as raw, physical decay.

Table 6 - OLS Models Predicting Change in Calling Rates - Three Models

Global Model - OLS Regression - Predicting Physical Disorder, Social Disorder, and Emergency Social Disorder Call Rates

	Model 1 - Predicting Physical Disorder Calls			Model 2 - Predicting Social Disorder Calls			Model 3 - Predicting Emergency Social Disorder Calls		
	Coefficient	*t*- Statistic	SE	Coefficient	*t*- Statistic	SE	Coefficient	*t*- Statistic	SE
Intercept	-0.022250 ***	-12.275661	0.001813	0.003261 ***	4.364414	0.000747	-0.019553 **	-3.326656	0.005878
Median household income	0.000000 ***	-3.477123	0.000000	0.000000 ***	-8.886091	0.000000	0.000000 ***	-0.124949	0.000000
% Population Black	0.011936 ***	12.472594	0.000957	-0.006247 ***	-15.903745	0.000393	0.002816 **	0.907223	0.003104
% Families living in poverty	-0.015231 ***	-5.375858	0.002833	-0.005692 ***	-4.885475	0.001165	0.049468 **	5.399122	0.009162
Ratio High school to Bach. [a]	-0.000135 **	-3.720119	0.000036	-0.000060 ***	-4.023290	0.000015	-0.000262 ***	-2.230276	0.000117
% Unemployed population	0.056874 ***	5.755118	0.009882	0.037142 ***	9.148940	0.004060	0.095025 *	2.971906	0.031974
% Foreign-born population	-0.043546 ***	-6.843823	0.006363	0.013908 ***	5.313609	0.002617	-0.014487 **	-0.703391	0.020596
% Residents not moved in 5 years	0.025141 ***	9.827780	0.002558	-0.003097 **	-2.939036	0.001054	-0.011333 **	-1.367347	0.008288
% Vacant residential houses	0.074078 ***	22.590787	0.003279	0.012192 ***	8.967907	0.001360	0.081725 *	7.640055	0.010697
% Resident-owned houses	0.019005 ***	10.507385	0.001809	0.003955 ***	5.309531	0.000745	-0.006139 **	-1.047385	0.005862
Population Density	0.000001 ***	18.784960	0.000000	0.000000 ***	12.092139	0.000000	0.000001 ***	6.589891	0.000000
Rate Calls Physical Disorder	-----	-----	-----	0.127562 ***	52.418011	0.002434	0.734288 **	37.451201	0.019607
Rate Calls Social Disorder	0.754409 ***	52.418011	0.014392	-----	-----	-----	0.114017 *	2.329057	0.048954
Rate Calls Emergency Social Disorder	0.070209 ***	37.451201	0.001875	0.001843 **	2.329057	0.000791	-----	-----	-----
Rate Calls 911 Crimes	0.280840 ***	20.799863	0.013502	0.151031 ***	27.366028	0.005519	2.799435 *	69.234287	0.040434
Number of Observations:	25818			25818			25818		
df:	25804			25804			25804		
Joint F-Statistic:	1033.590291			612.219603			954.851381		
Prob(>F), (13,25804) df:	0.000000 ***			0.000000 ***			0.000000 ***		
Akaike's Information Criterion (AIC):	-88493.311212			-134380.375293			-27887.352710		
Multiple R-Squared:	0.342417			0.235728			0.324804		
Adjusted R-Squared:	0.342086			0.235343			0.324464		

[a]Ratio of those completed a high school diploma to bachelor's degree, divided by local population 25 years and older

*p < .05; ** p < .01; *** p < .001 (two-tailed tests).

The Percent Foreign-born" and "Percent Families living in Poverty" variables reveal mildly suppressive effects on rates of calling with negative coefficients of -0.044 and -0.015, respectively, indicating decreases in the call rate of about 4 and 1% respectively for each 1% increase of these factors. The coefficient for poverty might be deemed small, but one must consider the wide fluctuations of poverty rates across the city at times means some places have no families living in poverty while in other spaces they experience rates reaching and exceeding 80%. Accordingly, when poverty reaches an 80% threshold we can predict it will suppress calls about physical disorder *almost one and half times as often* as well-off neighborhoods.

Predicting 311 Call Rates for Social Disorder Using the OLS Global Model. The OLS model produced an overall explanation of variance in 311 Calls for Social disorder with an adjusted R2 = 0.235, F (14, 25804) = 612.22, p <.0001. This is considerably less predictive in strength compared to the 0.342 R2 found for the physical disorder call rate prediction model. It suggests, first, that additional mechanisms are excluded in this model's specification. As above, the rate of calls is predicted by all fourteen variables, all at a p <.001, except "Percent Residents not Moved in 5 years" which is significant at p<.01. Additionally, median household income, education, and population density contribute little to the explanatory power of this model. The two strongest predictors for variance in 311 Calls for Social Disorder rates were rates of calls made for 911 crimes and calls made for remediation of community physical disorder. "911 Calls for Crime" rates were significantly, positively predictive of increased rates in calling about social incivilities, though about half as strong in impact as the previous model when predicting physical disorder call rate changes. For every tenfold increase in the rate of calls being made about issues of physical disorder we see a translation into a one unit increase in the rate of calls being made about social disorder problems. Whether residents own their home and the numbers of vacant homes figure significantly less here than the first model, indicating that physical housing stock, and its ownership ratio, impacts calling about physical environment issues more than social and incivility issues.

Moving from predicting physical disorder call rates to social disorder call rates we can see a reversal of direction for several of the parameters' coefficients signs. The variable 'Percent Black' while positive in the prediction of physical disorder calling (0.0112) becomes a negative, or suppressing, parameter in the second model (-0.006). The same is true for "Percent of Residents not moved in 5 years" which is positive in the first model but weakly negative in the second. Foreign-born population, negative in the first model becomes significant, though weakly positive in predicting whether or not people call about social disorder in the city.

Predicting 911 Call Rates for Emergency Social Disorder Using the OLS Global Model.

In the final model I tested predictor variables on the dependent variable "Rate Calls 311 Emergency Social Disorder". Such calls are those in need of immediate redress, generally by police, including drug activity and "suspicious persons", but also more minor incivilities like noise complaints, disorderly persons and "juvenile disturbances". Overall predictive power increases to levels similar to the first model with an recorded adjusted R2 of 0.324, $F(14, 25804) = 954.85$, $p < .0001$. The parameters 'Percent Unemployed', 'Percent Vacant Houses', 'Rate Calls Social Disorder', and 'Rate Crime Calls' all become less statistically significant in their contribution to this model with all variables sharing a lower p value, 0.05.

As in the previous two models income and education contribute little to prediction overall, but population density now, though a weak predictor, is significantly positive in its correlation to increases in global call rates about emergency social disorder issues. Race has the least significant positive impact on call rates in this model compared to the three models here while "Residents not moved in 5 years" and Percent of residents Foreign-born" account for little of the overall explanatory power. Of interest is the observed increase in predictive power *and change of direction* for the variable "Percent of Families living in Poverty". In this last model it now predicts increases in call rates where before it suppressed them. Accordingly, this model predicts, for every 1% increase of families living in poverty in an area, there is a corresponding 5% increase in the rate of emergency social disorder call rate by area residents.

The highest predictive factor here, as in other models, is the positively significant sign for 'Rate Calls 911 Crimes' with an observed value of 2.799. Therefore, for every 1 unit increase in the rate of calls made for 911 crimes calls, we can expect an almost *three fold* increase in calls for "emergency social disorder" problems. While this might come across as simply "logical" it is important to point out that the two categories are fundamentally different by definition. 911 emergency social disorder calls encompass those actions *perceived* to be of threat or a crime, while the 911-

crime calls rate includes only those calls *legally codified* as criminal acts – and identified as such by police, not residents[15].

Tests for Multicollinearity in OLS Modeling

Determining Spatial Influence Extents for Model Parameters. After running the OLS models the generated residuals from each were plotted in histograms to determine if there were any significant issues with heteroskadasticity in the data. None were revealed that indicated compromised data. As a final data test to determine if there were any issues with spatial influence on model outputs I plotted and mapped the OLS residuals themselves, looking for spatial autocorrelation (clustering) of error terms to detect multicollinearity issues. This analysis step helps set the "moving window" or the spatial reach, measured from a local, addressed, point, that will encapsulate a sample population within it, used in the final, spatial, geographically weighted regression models. Within a spatial extent window a mean is calculated, then moved to the next data point, and so on, moving from one observation to the next, all across the map face, all while comparing the observed, local, mean to expected, local, and global mean values. As above, when analyzing the input variables separately across the neighborhoods for divergence of values (clustering types, and significant clustering patterns) each of the OLS Call Rate models' output residuals were tested using Moran's I, z-scores and LISA measures. This to determine if error

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[15] For example – if a resident calls about a 'prowler' that will be coded by operators as a *threat* to be investigated, but not a crime until it is confirmed as such by police. In contrast if a resident calls to say "I've been robbed" or "assaulted" the event is coded as a "crime" by operators and requires immediate police intervention.

terms were diverging, what if any patterns existed and were they occurring with a degree of significance.

The initial mapping of OLS residuals (see Figure 32) in a global model reveals little divergence in z-scores across the spatial plane for the neighborhoods of interest. For the OLS model predicting 311 Physical Disorder Call rates (top left) the error terms cluster somewhat in the Federal Hill neighborhood, but not particularly so in the Sandtown neighborhoods. The OLS residuals for predicting 311 Social Disorder Call rates (top right) diverge very little from the expected terms. However, mapped *z*-scores for the model predicting changes in Emergency Social Disorder Call rates, does show some divergence of OLS error terms in the Sandtown area, mostly in the northern Upton neighborhood but again, not particularly clustered perhaps, which I test next. The bottom right map, showing the mapped residuals for the prediction of variance in 911 Crime Calls shows no significant divergence in error terms as mostly grey and white squares in both neighborhoods.

Tests for local indicators of spatial autocorrelation (LISA) were performed on the mapped z-scores, to better reveal whether any of the models displayed significant issues with spatial clustering of error terms and what those patterns might be (see Figure 33). In the upper left map, the map of 311 Calls for Physical Disorder rates show clusters of red blocks, or HH values, indicating high error terms are clustering about other high error terms in both the Sandtown neighborhood and Federal Hill clusters notably revealing clusters of error terms that were previously hidden in the first mapping of z-score values.. Virtually no cluster patterns appear in either neighborhood when mapping error terms from the predictive model for 311 Calls for

Social Disorder (top right) while the same holds true for the mapped error terms for 311 Calls for Emergency Social Disorder. Finally, high error terms, surrounded by others high values, also appear in Sandtown-Winchester and Druid Heights neighborhoods in the bottom, right, map for "911 Crime Calls" rates (Figure 34).

Outputs of GWR Local Statistical Modeling Predicting Call Rate Changes

Using Geographic Weighted Regression (GWR) the final analyses produced spatially-derived coefficients predicting the effects of the independent variables on the dependent variables in each of the three call rate prediction models. GWR results do not focus on one, universal, regression equation though one is produced for reference of local measures to a global one. Rather, focus is on the statistical analyses that produce *individual regression outputs at every cell* and specifically weighted by area neighbors, and their observed values. It is from these that local values are derived and the universal measurement, or a spatially weighted R2 value **(**see Table 6 - OLS Models Predicting Change in Calling Rates - Three Models**).** The adjusted R2 for “311 Physical Disorder Calls” was 0.429, very strong, while for “311 Social Disorder” the R2 = 0.220, and finally, for “911 Emergency Social Disorder Calls” it measured 0.272. I compare these spatial results with the aspatial OLS model results below after recounting results of final statistic tests for normal distribution of these outputs.

Table 7 – GWR Results and Diagnostics: The Three "Calls for Service" Models
Geographically Weighted Regression Results and Diagnostics by Calls for Service Models

	Predicting 311 Physical Disorder Calls	Predicting 311 Social Disorder Calls	Predicting 911 Emergency Social Disorder Calls
Bandwidth*	2916	2963	2900
Residual Squares	1.16415635318	2.25605353148	66.66211564480
Effective Number**	14.50829640930	14.04253305790	13.95479212690
Sigma	0.05135046526	0.07252163457	0.40618564058
AICc***	-1402.90064742000	-1057.18209569000	443.56636161300
R^2	0.42916314522	0.22407697104	0.29443393546
Adjusted R^2	0.41169728261	0.20048488433	0.27181156173

*Measured in feet, the moving, weighting, window used in the GWR computational analyses, that captures local, neighboring values to compare against the observed value.

** Measured as the number of parameters used in the GWR model (Mount 2009)

***Akaike Information Criterion

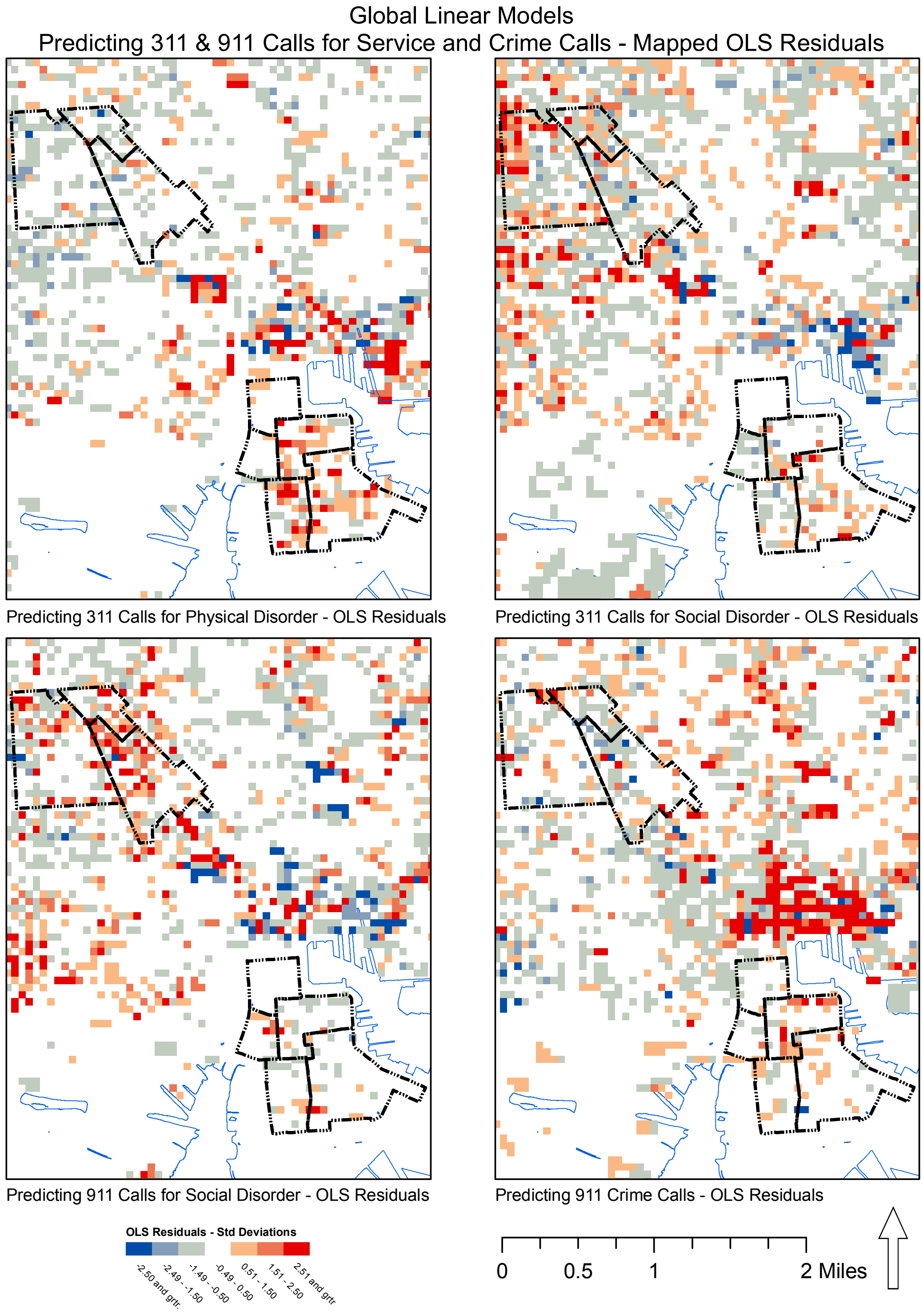


Figure 32 – OLS/Global Linear Regression Model – Mapped OLS Residuals

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

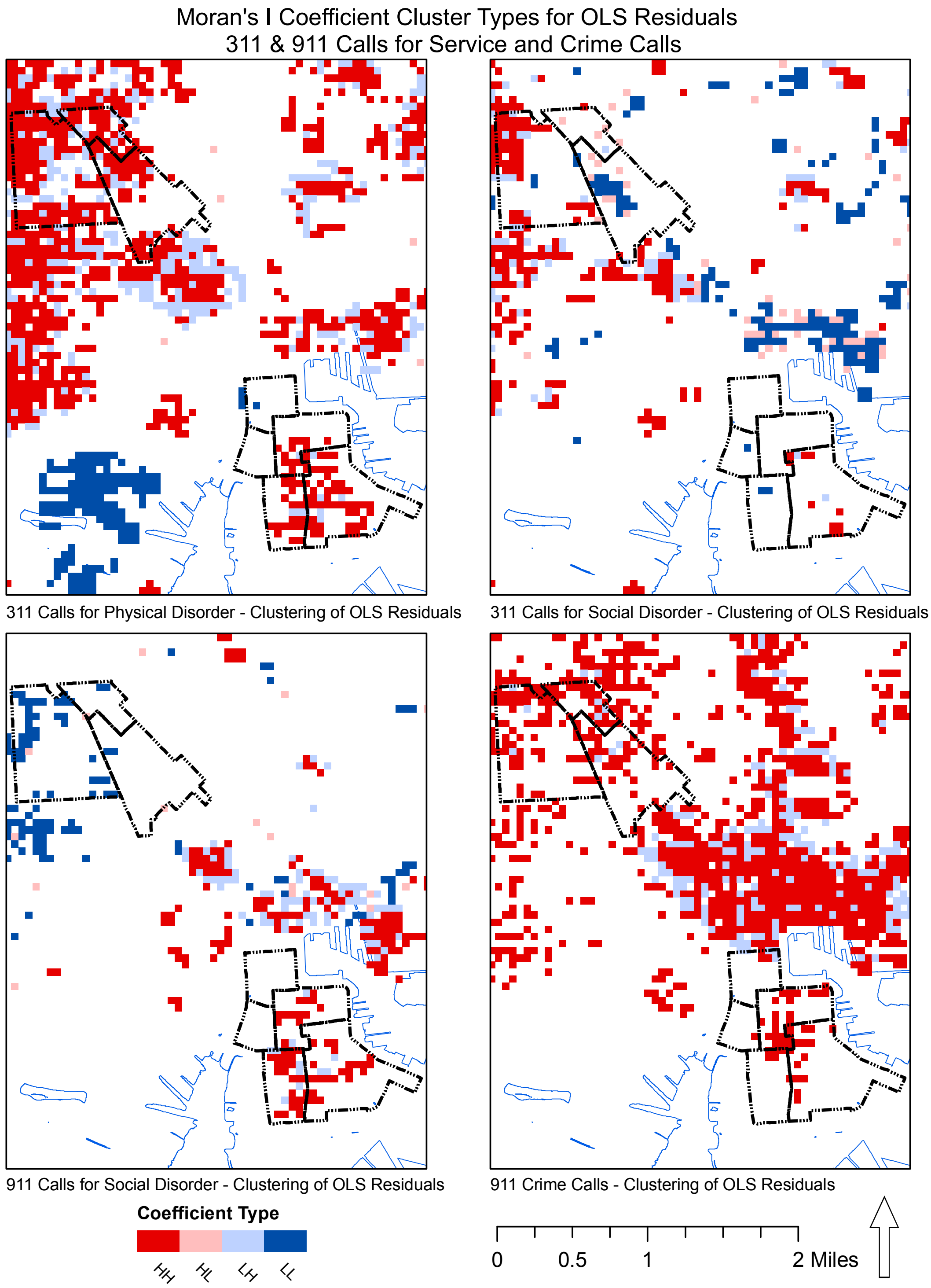


Figure 33 – OLS/Global Linear Model – Moran's *I* - Mapped LISA Coefficient Cluster Patterns

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

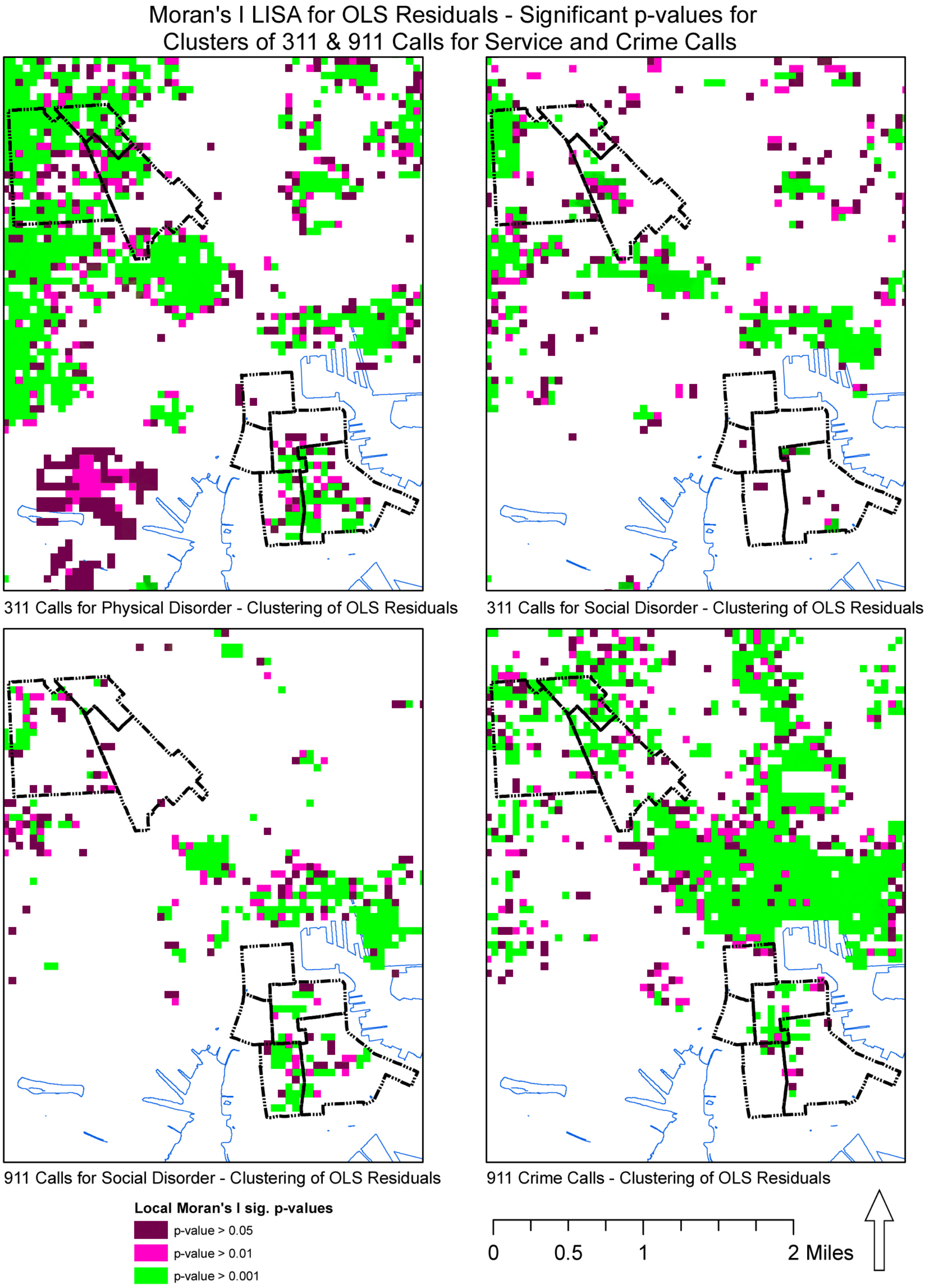


Figure 34 – OLS/Global Linear Model – Moran's *I* – Mapped tests of significant clustering using *p*-values.

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

Both the Physical Disorder and 911 Crime Calls map (see Figure 34, top left and bottom right) display large swatches of bright green color – an indication of clustering with very high statistical significance (p <.001). Clustering of the high error values about other high values seen in Figure 33 is not by chance alone. Rather, local influences on data are jeopardizing the validity of these two models' results, particularly for the OLS model attempting to predict changes in 311 Physical Disorder call rates , and especially in the Sandtown-Winchester neighborhood in the north. Accordingly the global model predicting these call rate changes should be interpreted warily -- generalizability of results in this particular neighborhood is questionable at best. At the same time these test reveal why weighting of data, using a spatial frame is important. The data then are weighted for the GWR (see discussion on semi-variorgrams on page 103). The remaining maps show some significant areas of clustering by nothing particularly damaging to the OLS models' integrity. In all these maps highlighted the need to attend to the final parameter settings for the geographic weighted regression, which follows, to correct for the spatial non-stationarity, the spatial non-normality, of the distribution error terms when creating predictive models. Next then are the findings from the GWR, spatial, which tried to explain what influences changed the various models' call rates.

In each call rate predication model the term "bandwidth" denotes the spatial extent of influence determined from earlier calculations using semivariograms (see page 103) and was subsequently employed in the GWR calculations to account for any spatial influence local values had over their immediate, neighboring, observed value being calculated within the GWR. When predicting call rates all models are not equal in error terms produced. Error terms show appreciably higher values in the '911

Emergency Social Disorder' calling rate model (residual squares were reported as 66.66) when compared to the other two models where error terms were recorded as 1.16 and 2.26 for the '311 Physical Disorder' and '311 Social Disorder 'call rate predication models respectively. This indicates some issue with the predictive variables in the former 911-call model.

In regression diagnostic output a lower Akaike Information Criterion (AICc) value indicates increased model strength and coherence (Burnham and Anderson 2002). Here, in all three models, AICc values were *substantially* reduced when compared to the AICc values generated in earlier OLS model runs (see Table 8). Since lower AICc's are relatively "better" we can say the GWR models have improved the model predictive strength, and thus specification, by accounting for spatial influences on locally recorded values when compared to the aspatial, local, OLS modeling.

Compared Global (GWR) and Local (OLS) Strengths of Prediction as Statistical Methods

Looking at the predictive power of each call rate model and comparing the GWR results to the earlier OLS results (see Table 8) we see when predicting call rates for '311 Physical Disorder' the resulting GWR R^2 produced was 0.429 with an adjusted R^2 was 0.412. This is substantially higher than the earlier generated, OLS model's, R^2 of 0.34 (adjusted R^2 0.342). GWR R^2 measures for '311 Calls for Social Disorder' were 0.224 and adjusted R^2 of 0.200 respectively, slightly lower than the earlier OLS R^2 of 0.236 (adjusted R^2 0.235) while, when predicting calling rates for '911

Table 8 - Predicting Call Rate Changes in Three Models: OLS Global vs. GWR Local Statistics Compared

	OLS Global Statistic			*GWR Local Statistic*	
Model Predicting Changes in Rates for…	Adj. R2	F statistic	*p*-value	Adj. R2	AICc*
311 Physical Disorder Calls	0.342086	1033.59	0.000000	0.411697	-1402.90
311 Social Disorder Calls	0.235343	612.22	0.000000	0.2004849	-1057.18
911 Emergency Social Disorder Calls	0.324464	954.85	0.000000	0.271811	443.56

*Akaike Information Criterion - Lower numbers indicate increased model strength and coherence

Emergency Social Disorder', the GWR determined R^2 was 0.294 while the adjusted R^2 was 0.272. This is quite a bit lower than the OLS estimates of $R^2 = 0.325$ and adjusted R^2 of 0.324. The decreases in R^2 values however are offset by the large reductions of the AICc values for all models. This shift indicates that while the GWR modeling predicts with slightly less strength we have better *confidence* variable coefficients are what we they say they are in all the call rate prediction models.

Mapping GWR Variable Coefficient Values – Between Model and Between Site Variations.

After running GWR models each cell across the spatial plane is assigned a local coefficient measure for each variable term in that model. In "Mapping the Results of Geographically Weighted Regression (Mennis 2006) Mennis notes the need to explore our research results by mapping the different variables of our models to reveal interesting patterns and, as such he admits, that this stage is part science, and part cartographic art. The maps below then are simplified, and color coded, to display relative coefficient strength[16] across a locality. This helps to visualize spatial patterns to help identify local "coefficient hotspots" while aiding in the ability to cross reference one map to another to detect similarities and differences in outputs. The "science" side permits us to view these spatial variations as important local variations in coefficients – GWR generated and mapped model coefficients that show variations in the local values that OLS global models, using aggregate measures, would otherwise miss. Accordingly, what follows is the mapping of each of the independent

[16] Caution is stressed here in interpretation of these maps – Each maps displays *relative coefficient strength* for a given variable. Mapped coefficients show relatively strong support of prediction (red values) *or suppression* (blue values). However, variables mapped from one model to the next are <u>not</u> generally indicative of similar <u>values</u> when shaded the same color – only that they display similar variation in *degree* and range of influence given the banding and spectrum of colors shown.

variables, their associated, locally predictive, coefficient values, as generated from the GWR modeling outputs. Each page is displayed in triptych style– three maps of one variable's coefficients, with one map for each of the three call rate prediction model types. I highlight the main findings and observations, including one example map, the remaining maps to be found in the in the appendices. I close with a summary chart to illustrate the global implications these variations in coefficient direction and strength show us about the separate call rate prediction models, as well as how the variables produce different values between the two different local spaces of interest.

In the first of the independent variable coefficients mapped, to observe spatial differences in the dispersion of strengths and directions values, "Percent Black (Population)" (Figure 35) shows that in each of the three call-rate predictive models there are differences in the degree of coefficient predictive power - and when comparing Sandtown to Federal Hill. When used as a variable to predict calls for physical and social disorder the coefficient values generally increase in a negative direction (suppressive of calls) (see maps left and center) and are depicted as colored blue and drab green. But the variable displays markedly higher, and positive support (it enhances call rates) for the model used to predict changes in the rate of calls for emergency social disorder. Positive impact on call rates is especially so in the Sandtown cluster of neighborhoods that appear blanketed largely in dark red (right map). Generally speaking, race has a suppressive to neutral effect on whether or not people call more about physical and social disorder issues, and a relatively strong, and positive effect, enhancing call rate prediction, when it is used to determine changes in call rates for 'Emergency Social Disorder' issues.

Mapping coefficients from the education variable (see appendices, Figure 61, page 281) we see its effect is relatively neutral, in both neighborhoods, when used to predict changes in calls about physical disorder. When looking at social disorder calls however the impact is more pronounced, and while it appears as suppressive in Federal Hill it is noted that the education variable produces an inverse value: the higher the number of bachelor's degrees relative to high school diplomas the lower the locally observed value. This map then illustrates how as education increases there is a relatively strong increase in this variable predicting increases in calls about social disorder. In the final education map both neighborhoods are largely red and orange indicating that as residential spaces are less educated there are increases in calls for emergency social disorder – and this holds true in both neighborhoods equally.

The variable "Percent Foreign Born" () presents a much more varied dispersion of coefficients comparing the three different models. When used to predict '311 Calls for Physical Disorder' both neighborhood sites are mapped largely with coefficient values below 0.30, but the northern area of the Sandtown group shows very high predictive coefficients, suggesting as concentration of foreign born persons increases we will very likely see increases in calls about physical disorder. However, note that this does <u>not</u> hold true for south and east of Federal Hill where we know the proportion of residents to be relatively high in multi-ethnic and racial backgrounds. This demographic appears to be "activated" though when predicting '311 Social Disorder Calls' where suddenly predictive coefficients are extremely strong and positive, while <u>not</u> in Sandtown.

Measures of neighborhood stability (Percent Not Moved in Last Five Years,) demonstrate their strongest impact when determining increases in call rates for '911 Emergency Call' rates, but have much less impact in Sandtown. Median income appears to suppress calling about physical disorder, in both Sandtown and to a lesser extent Federal Hill, and when predicting increases in emergency social disorder calling Sandtown, deeply impoverished, is blanketed in crimson – an indicator of highly positive coefficient strength, while Federal Hill is largely "neutrally" affected by this variable. The percent of families living in poverty substantively influences whether or not Federal Hill residents call for issues about physical disorder, but that does not affect residents of Sandtown neighborhoods. Looking at '311 Social Disorder' we see, again, in the north poorer neighborhoods they are largely unaffected by the number of families living in poverty and whether or not they choose to call. However, the *opposite* is true in Federal Hill, which displays strong positive correlations for this variable. For emergency social issues the differences largely disappear however – larger numbers of impoverished families lead *both* neighborhoods to demonstrate higher rates of calling to stem the tide of injurious or dangerous actions locally.

The variable "Percent Unemployed" () exhibits weak association and predictive coefficients in Federal Hill when predicting '311 Physical Disorder' call rates, while somewhat stronger coefficients are seen when the same variable is used to predict '311 Social Disorder Calls' and emergency calls. Vacant houses () prove to be a strong coefficient predictor of '311 Physical Disorder' calls in the Sandtown cluster but <u>not</u> in Federal Hill. However, when the same variable appears, predicting call

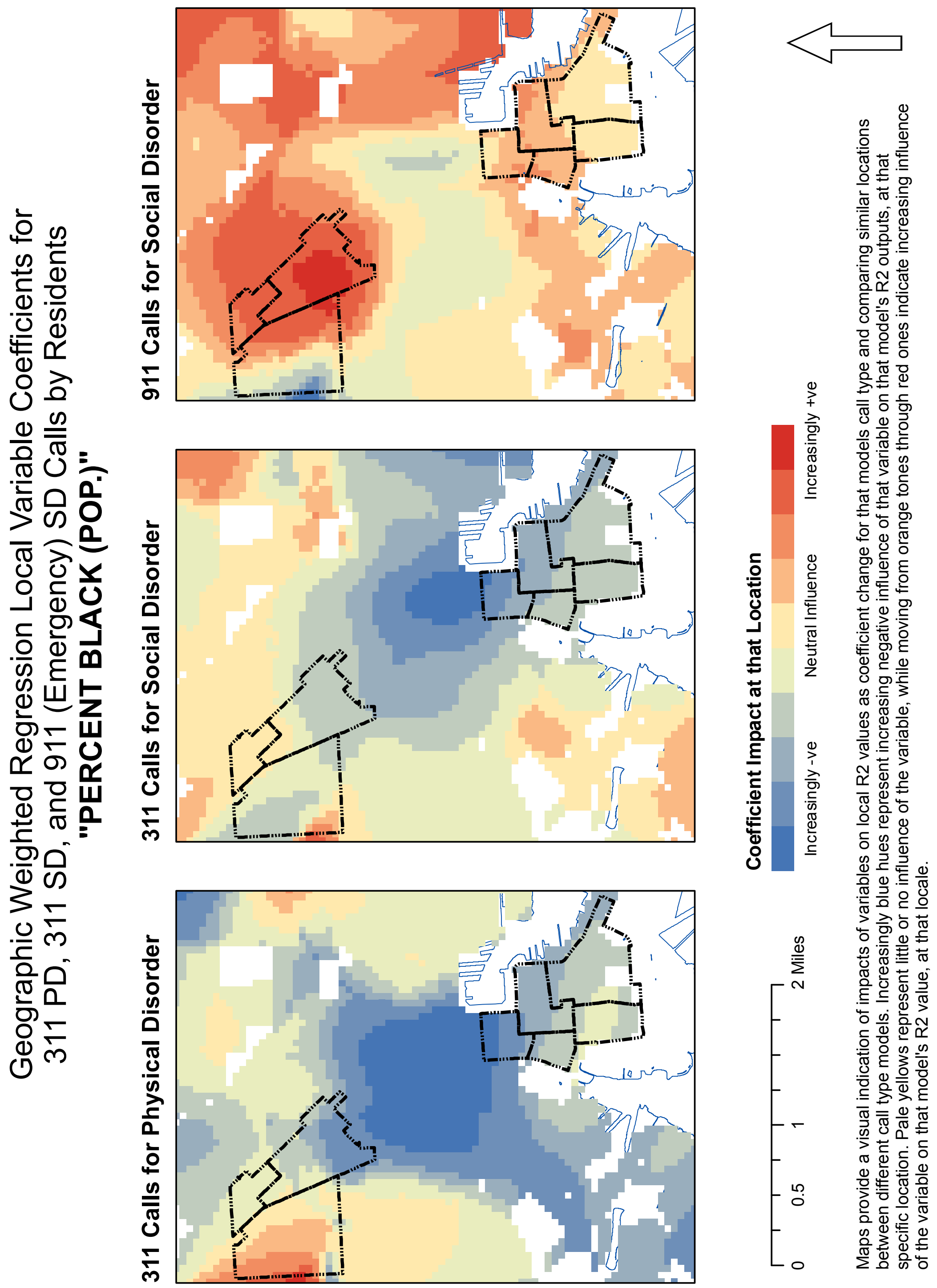


Figure 35 – Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent Black(population) (rate adjusted)

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

rates variance for social disorder, it is the Federal Hill neighborhood area where it is strongly positively, and enhancing of call rates. Finally, when predicting emergency call rate variation vacants contribute relatively little in explanatory power, in both neighborhoods, with some suppressive characteristics on those rates found namely in Federal Hill. Mapped homeownership () variable coefficients show a *very* strong enhancing effect on rates of calls about physical disorder in Federal Hill – the strongest amongst <u>all</u> variables and <u>all</u> models in fact – while the variable is neutral in the Sandtown group. Interestingly though, owning your own home has a much lower effect on whether one probably calls about issues of social disorder or emergency social disorder, comparing the Federal Hill and Sandtown spaces. "Population Density" strongly predicts increases in call rates about physical disorder – but only in Federal Hill (see). It's relatively neutral predicting changes in social disorder calls but *negative* when predicting call rates for emergency social disorder, again mostly in Federal Hill – as population density decreases there is a relatively strong likelihood that call rates also go down.

One of the most striking differences in mapped local-site coefficients is found in those structured by the variable "Crime Rate – Part I Crimes" 911 Crime calls predict little about rate changes in Physical Disorder calls made in either neighborhood space, and remain relatively neutral to slightly positive, when predicting calls about general social disorder. However, when looking at how they relate to "Emergency Social Disorder Calls" Sandtown-Winchester, Upton, and Druid Heights are awash in a sea of red – highly positive coefficients indicating as heavy calling about serious crimes occurs so does calling for more general, non-police, emergency calls. This might sound unsurprising but recall that the two call types are distinctly different – one is crime classified by *police* the other is an appraisal of being under threat, made by residents trying to stem a crime action perhaps. Clearly this suggests the two are connected here. But in Federal Hill, where crime obviously happens though perhaps at a much lower rate, it does not appear to be linked to changes in call rates about the most bothersome kinds of social disorder.

Finally, seeing how the other call rates themselves might impact other models' rates increased rates of "311 Calls for Physical Disorder" () are highly, positively, predictive of associated other higher call rates for *both* '311 Calls for Social Disorder' *and* '911 Calls for Emergency Social Disorder' … but only in Federal Hill. (see). In contrast, however, coefficient values for "311 Calls for Social Disorder" have a positive and strong association for increases call rates about physical disorder in the Sandtown area (see) while this same variable suggests that call rates for physical disorder and emergency social disorder decline in Federal Hill when they go down as well. This is largely as social disorganization theory would predict – the higher disorganization in the Sandtown neighborhood is reflected in the associated call rates while, in Federal Hill, where disorganization is lower, we see decreasing call rates linked to other decreasing call rates. Lastly, mapping the variable coefficients for "911 Emergency Social Disorder Calls" () we see the detrimental effect an environment of crime might have on residents as '311 Calls for Physical Disorder' are largely suppressed, reduced, in Sandtown, and to a lesser degree in Federal Hill. In fact this variable appears to be the most universally suppressive amongst all variables. It does not seem to be linked to general social disorder calling however, where, in both neighborhoods, residents are relatively neutrally affected in their likelihood to call more or less about emergency social disorder problems if they are already calling about non-emergency ones.

Compared Global (GWR) and Local (OLS) Predictive Coefficients Within Each of the Three Calls for Services Models.

While GWR does not generated one predictive regression equation, but rather specific and local ones for every cell across space, it is possible to look at a local aggregate of values – in this case aggregating those within the boundaries of the Sandtown and Federal Hill neighborhood clusters – to explore differences between two localities. This is not the same as simply taking aggregate averages of say, a census tract, because in this case the values have been weighted, and adjusted, depending on other neighboring values of interest. In these last exploratory analyses steps then I aggregated the neighborhood specific GWR-generated coefficient values for each of the three different call rate models, creating two comparative coefficients from each neighborhood cluster group, and plotted them alongside each other and the earlier-generated OLS model's predictive coefficients. In this manner we can view, graphically, the OLS, globally generated coefficients with GWR, locally generated, coefficient results, for all independent variables. We can see how results differ by statistical approach, the three call models and by neighborhood cluster.

Accordingly, the figures presented below, (Figure 36), include three values: one for each independent variable in each of the three predictive call models to illustrate their relative strengths to one another at a neighborhood site, and for each of the different call types.. A "triangle" symbol represents the OLS, or global model, coefficient of prediction, an 'S' symbol denotes the GWR local coefficient for the Sandtown cluster, and an ‘F’ symbol represents the same local GWR measure for the Federal Hill neighborhoods cluster.

Each chart includes a “zero” line - the level at which a coefficient is predicted to be neutral in impact on the dependent variable. Above that line values denote a predicted a positive coefficient impact on the dependent variable (an enhancement or increase in call rates by that coefficient magnitude) while values below that indicates suppression or decrease in call rates is predicted. This visualization illustrates too how coefficients change direction - including when comparing the global OLS vs. local GWR analyses methods, looking for differences in results between the two neighborhood sites, or, as summarized in the fourth and final chart, identifying differences between the three call rate models and the respective independent variables (see

Compared Global (GWR) and Local (OLS) Predictive Coefficients for the Model ‘Predicting Call Rates for 311 Physical Disorder.

When plotting variable coefficients from the OLS linear regression (global) results against the locally generated, neighborhood values, from the GWR statistics, we should see those values cluster all about each other if those OLS coefficients are truly, independent and unbiased estimates. If we witness GWR coefficients have divergence or spread from the OLS values then those original, OLS, observations were, somehow, spatially dependent, and hence they are not unbiased estimates – local influences were affecting those original OLS determined coefficient values. As well, differences seen in the plotted, variable parameter estimates, for the two neighborhoods themselves further illustrate how variables may operate differently in different spaces, due to other factors such as varying degrees of social and physical disorganization, demographics and so forth, that make those spaces different, and unique, shows the plotted coefficients that predict “311 Calls Rates for Physical Disorder”. Coefficients for the variables Education, Median Income, Percent Foreign Born, Lived in House for 5 Years, Population Density and ‘Call Rate for Emergency Social Disorder’ are very close to the original OLS global coefficient values and do not contribute significantly to the explanatory power of the model. Variables with the largest divergence from OLS values include the GWR aggregate local coefficient values (neighborhoods) for Percent Black, Percent Unemployed, Percent Houses Vacant, Crime Rate (911 Calls), and Social Disorder Call Rate. The ‘Percent Unemployed’ and ‘Percent Black’ coefficients show substantially higher, and positive impacts, on calls for ‘Physical Social Disorder’ in the Sandtown area (each is 0.066, and 0.063 respectively) while the same variable reports coefficients much less powerful, and negative, and so *suppressing* calls in the Federal Hill communities (-0.088 for ‘Percent Unemployed’, and -0.006, for ‘Percent Black’). Local coefficient values in Sandtown, for ‘Percent of Homes Vacant’, shows the GWR coefficient to be 2.4 times higher in predictive power and demonstrates how increases in the number of vacant houses can correspond to increased rates for Physical Disorder calls. When compared to the original OLS values, this shows a predictive coefficient *twenty-four times* higher than that found locally in the Federal Hill neighborhoods. A similar difference exists when tapping the role of ‘Crime Rate’ to predict ‘Physical Disorder Calls’ but the neighborhood values reverse – Federal Hill shows a much higher coefficient 0.315 – a value 2.4 times higher than in Sandtown, where that measure is 0.130. For every three-unit increase in the reported Crime Rate we can anticipate that in Federal Hill the residents’ rate of calls about Physical Disorder issues will *also* increase by a factor of 1. This means we would expect a minimum of six unit increase in the rate of crime calls in Sandtown to generate the same level of calls for ‘Physical

Disorder' we see in Federal Hill. Federal Hill residents appears to be is much more sensitive about changes in crime rate than their Sandtown neighbors to the north and to possibly connecting those two components as issues in need of correction.

The most dramatic difference in coefficient parameter measures, predicting variance in rate of calls for 'Physical Disorder' is found in the variable '311 Social Disorder Call Rate'. For the OLS global model the coefficient reported was 0.744 – for every one unit increase in call rates about 'Social Disorder' we could expect a 0.74 unit increase in the rate of calls about 'Physical Disorder'. However, the GWR coefficient for the Federal Hill cluster was reported as almost half this impact (0.394) while in the Sandtown cluster the GWR coefficient predicted changes in calls about 'Physical Disorder' with significantly more power than in Federal Hill with this variable - 7.3 times higher in fact. For every one unit increase in the 'Social Disorder Call Rate' in Sandtown this same neighborhood sees a three unit increase in the rate of calls for 'Physical Disorder' issues, and this rate is roughly *four times higher* than the OLS model predicted earlier. These results imply that residents in Sandtown are quite attuned to disorder experienced in their neighborhood and call about *both* physical and social disorder significantly higher than Federal Hill perhaps.

Compared Global (GWR) and Local (OLS) Predictive Coefficients for the Model Predicting Call Rates for 311 Social Disorder.

Of the three predictive call rate models the 'Calls for 311 Social Disorder' model shows the least overall variance between local, GWR, neighborhood and global, OLS predictive coefficient values, as well as a smaller range for those parameter estimates (see). Education, Income, Population Density, Percent of Homes Owned, Percent

Lived in Home for 5 years, and the '911 Emergency Social Disorder Calls' rate coefficients were all uniformly predictive comparing OLS and GWR statistics.

The GWR coefficients do show departures from OLS ones, particularly for the following variables. 'Percent Black' shows a much higher suppressive effect, but only in Federal Hill – so there is some evidence that in neighborhoods that are more highly populated with African American persons calls for remediating 'Social Disorder' decrease. While the coefficients for 'Percent Families Living in Poverty' is roughly the same for the OLS model and the GWR model for Sandtown, in Federal Hill the coefficient is markedly higher, and reversed in direction. For every unit increase in families living in poverty in Federal Hill we see a three percent increase in rates of calls about 'Social Disorder', whereas in Sandtown this variable explains little. Unemployment shows strong positive prediction in 'Social Disorder' call rates in Federal Hill but less in Sandtown, as does the 'Percent of House Vacant'. The OLS model appears to have significantly overestimated the power of the variable 'Crime Rate' to predict changes in the 'Social Disorder' call rate where its coefficient was about 0.125 while the GWR results for the neighborhoods were both closer to 0.08. Interestingly the local GWR coefficients for the two neighborhood groups, for 'Percent Foreign Born', are quite divergent from the OLS one, but in completely different directions. In Sandtown foreign-born acts as a suppressing factor (-0.036) while in Federal Hill it is an enhancing one (0.059). Perhaps in Sandtown 'ethnicity' and 'diversity' undermine normative cohesiveness while in Federal Hill this racial diversity is seen as a positive neighborhood attribute – more of a melting pot rather than competition. The extreme spread of coefficients is, again, within the predictive

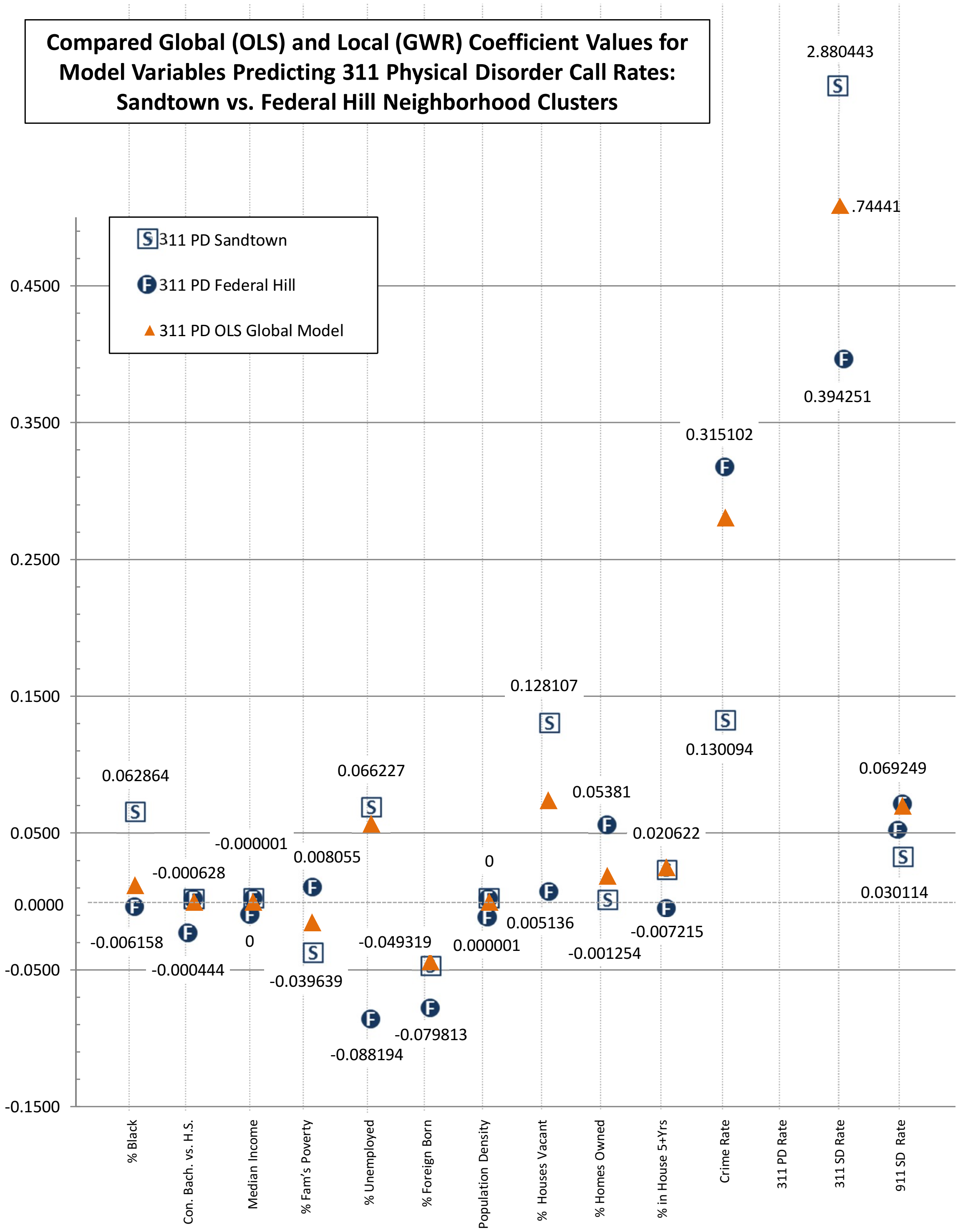


Figure 36 Compared Global (OLS) and Local (GWR) Coefficient Values for Model Variables Predicting 311 Physical Disorder Call Rate Changes: Sandtown-Winchester vs. Federal Hill

relationship between ‘Social Disorder Call Rates’ and ‘Physical Disorder Call Rates’. coefficients are not only different from the OLS value but different from neighborhood to neighborhood suggesting these rates may be quite dependent on locality.

Compared Global (GWR) and Local (OLS) Predictive Coefficients for the Model Predicting Call Rates for 911 Emergency Social Disorder

Comparing coefficient outputs from the OLS and GWR models, for the model predicting “Emergency Social Disorder “, we find a wide range of computed coefficients amongst all the three models. While some of the same variables show little variation from the OLS global model to the GWR model (namely, Education, Income, and Population Density) it also displays some striking differences between the two neighborhood spaces in terms of predictive coefficient power and directions. First, and most stark, are the extreme values for the coefficients for the parameter “Crime Rate”. While Federal Hill’s GWR coefficient is reported as similar to the OLS estimate at 2.297, Sandtown has a predictive value of 6.766 - or a predictive coefficient more than *three times higher* than Federal Hill’s, and the city’s, value. In Sandtown then a one-point increase in “crime rate” is predicts a *seven-point increase* in the rate of calls made about emergency social disorder. Sandtown’s coefficient measuring the effect of ‘Percent Foreign Born’ is four times higher than that found in Federal Hill, lending credence to the idea that this kind of local diversity is not seen as positive in that locale. When reviewing impact of ‘Rate of 311 Calls for Social Disorder’ on ‘Emergency Social Disorder Calls’ in Federal Hill the coefficient is spot on the citywide, OLS global value of 0.103 while in Sandtown the coefficient is 0.72 – or *seven times higher* of an effect in that neighborhood than in Federal Hill. ‘Physical Disorder Call Rate’ however is stronger, almost 2.5 times such, in contributing to increases in calls for 'Emergency Social Disorder' when one is in Federal Hill, compared to Sandtown. In Federal Hill every unit increase in call rate for issues about 'Physical Disorder' also predicts almost 1.5 unit increase in the call rate for 'Emergency Social Disorder'.

Perhaps most interesting for this model is how the coefficients for 'Lived in Home Less Than 5 Years' yields parameter estimates *different directions* for each of the two neighborhood sites while the OLS estimate showed <u>no</u> impact at all for this variable. In the south the neighborhood cluster of Federal Hill generated a coefficient of 0.09 versus a value three times more powerful, and negative for those living in Sandtown, or -0.30. Accordingly, in Federal Hill for every one percent increase in persons who have lived in their home for less than five years the model predicts a *nine percent* increase in calls about 911 Emergency Social Disorder. Again, these are call about things like 'suspicious persons', or 'drunk persons'. However, in Sandtown a similar increase for the variable 'Lived in Home Less Than 5 Years' predicts a *thirty percent decrease* in the call rate for 'Emergency Social Disorder'.

Analyzing for Directional Differences in Variable Impacts.

To better determine which variables had *directional* changes in coefficient impact on rates, and to explore how these variables affected each of the calling rate models differently, from the OLS to the GWR models, I plotted each model's coefficients - one for every variable – along side the OLS global coefficient value. This final figure (see) plots all three previous charts into one, combined illustration that visualizes the similarities and differences of all coefficient results. It permits a clearer comparison between the local and global parameter estimates while it highlights the variables with

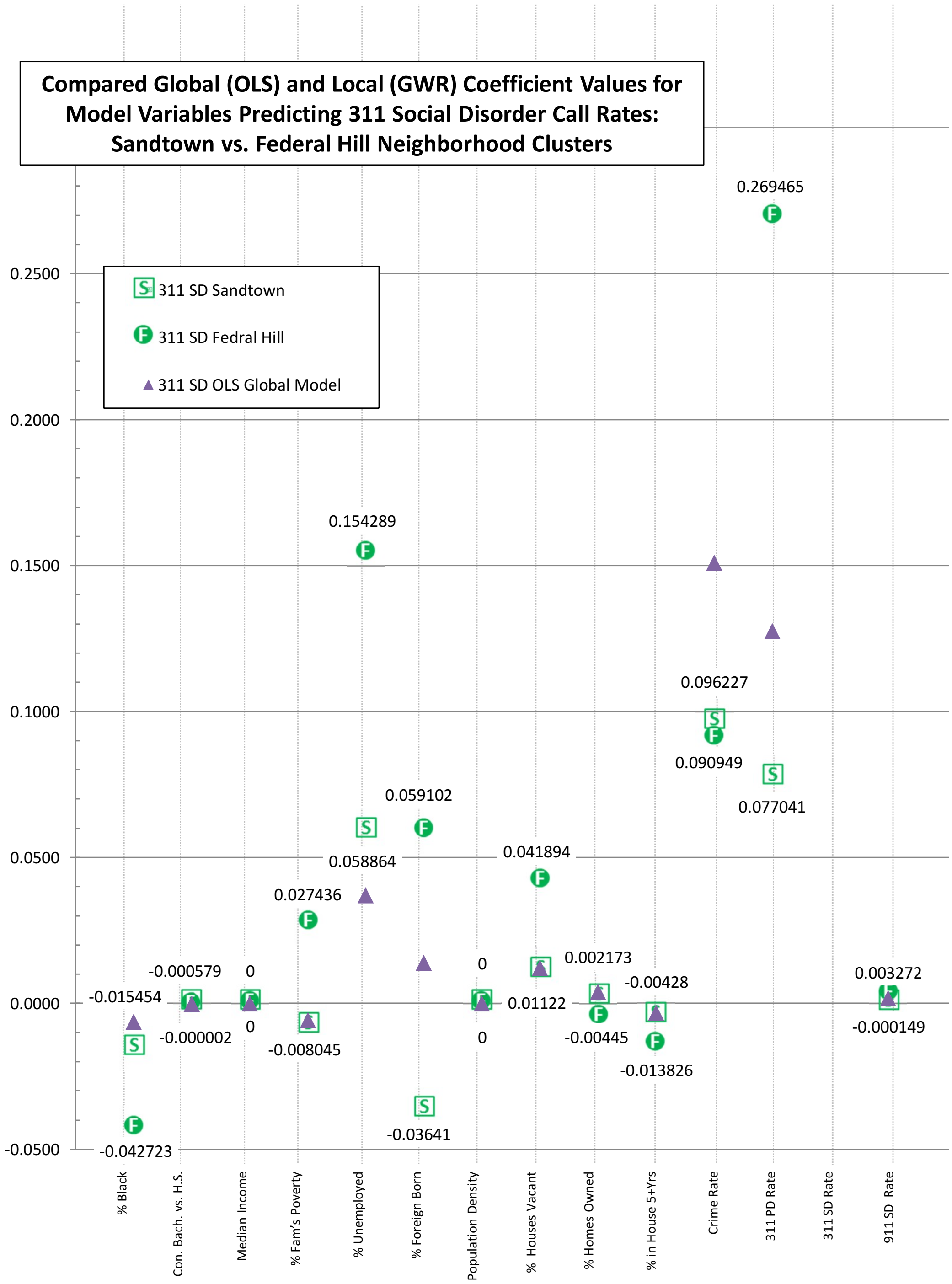


Figure 37 - Compared Global (OLS) and Local (GWR) Coefficient Value for Model Variables Predicting 311 Social Disorder Call Rates: Sandtown vs. Federal Hill Neighborhood Clusters

the most impact, those with the least while illustrating changes in parameter direction for variables between models and between the two neighborhood sites.

Across all three call rate prediction models, from global *or* local statistics, there was almost no variation, nor predictive power, demonstrated amongst the coefficients generated from the input variables for Income, Education, or Population Density, regardless of neighborhood location. Accordingly, the amount of income, the degree of education attained, and population density do not appear to contribute meaningfully to the prediction of any type of calling behaviors.

Assuming all calling behavior is motivated equally in all models we would expect all coefficients, for a given variable, across all models, to be similarly valued, though perhaps different between the globally-derived OLS statistics (denoted with 'x' symbols in the chart) versus the locally-derived-GWR results (denoted as 'S' and 'F' in the chart). For the most part this appears true with the OLS coefficients for the independent variables, for all three predictive call rate models, generally clustered about each other (see left area of chart in particular). But the OLS coefficients do not show similar values when predicting the impact of other call rates, especially when predicting '911 Emergency Social Disorder Calls' using 'Physical Disorder Call Rate' or predicting '311 Physical Disorder Calls' using 'Social Disorder Call Rate' as the predictor. In the first case, as an independent variable, 'Physical Disorder Calls' then is seven times stronger predicting positive variance in the rate of calls about 'Emergency Social Disorder' than it is when used to predict changes in the rate of calls for the nuisance generated 'Social Disorder Calls'. The same holds true for '311 Calls for Social Disorder' where they are about 7.5 times stronger predicting rate

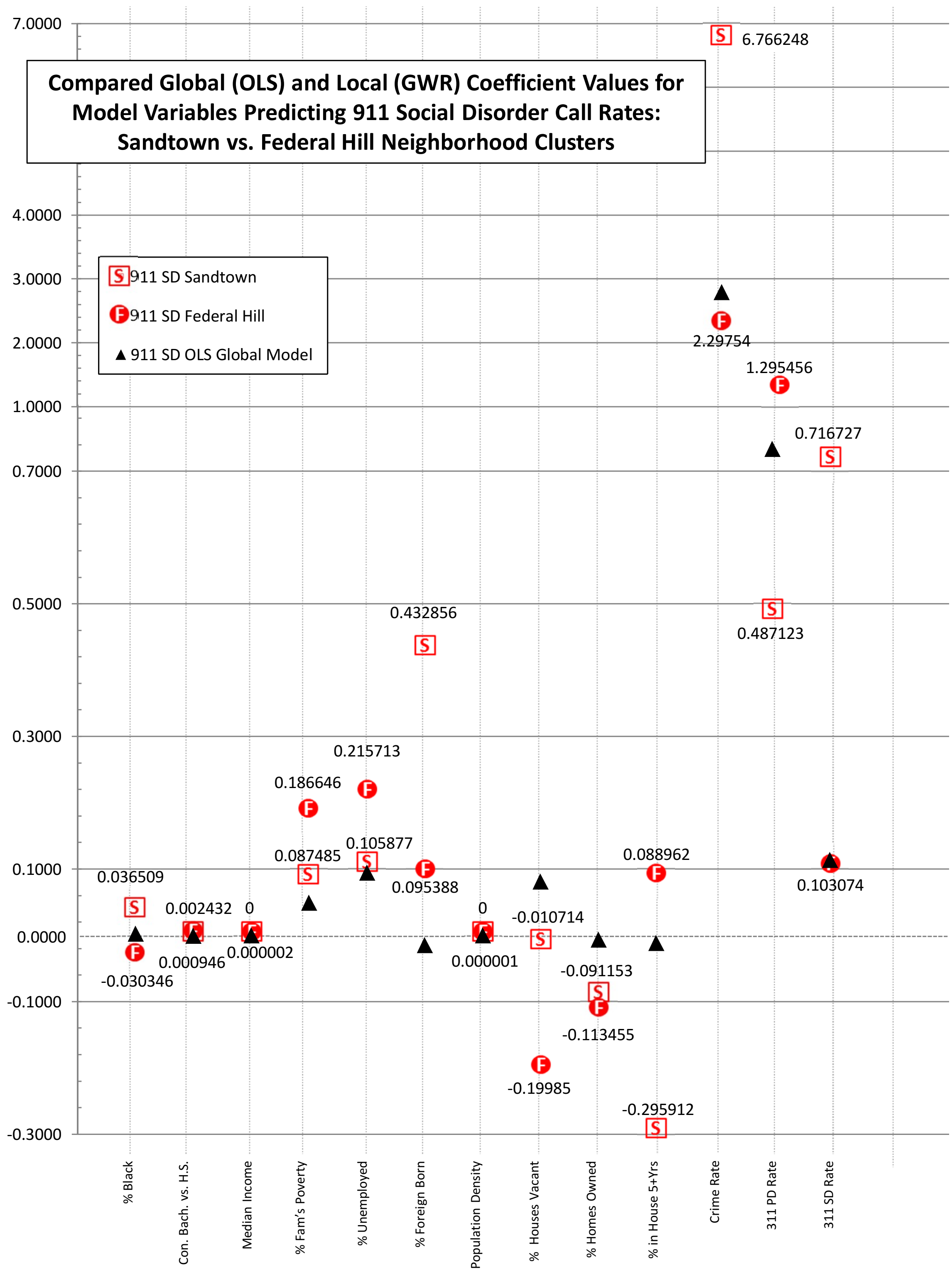
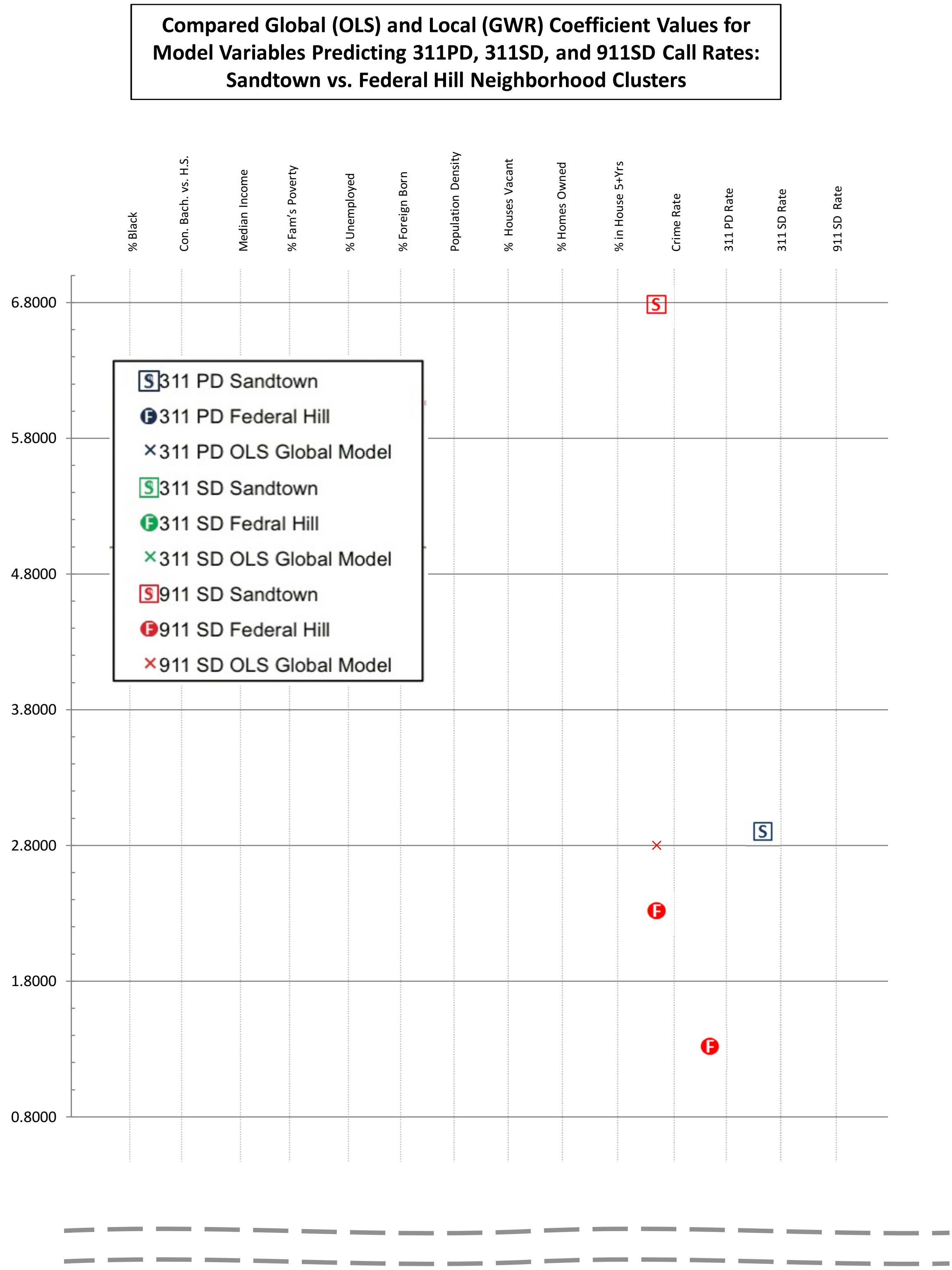


Figure 38 - Compared Global (OLS) and Local (GWR) Coefficient Value for Model Variables Predicting 911 Social Disorder Call Rates: Sandtown vs. Federal Hill Neighborhood Clusters



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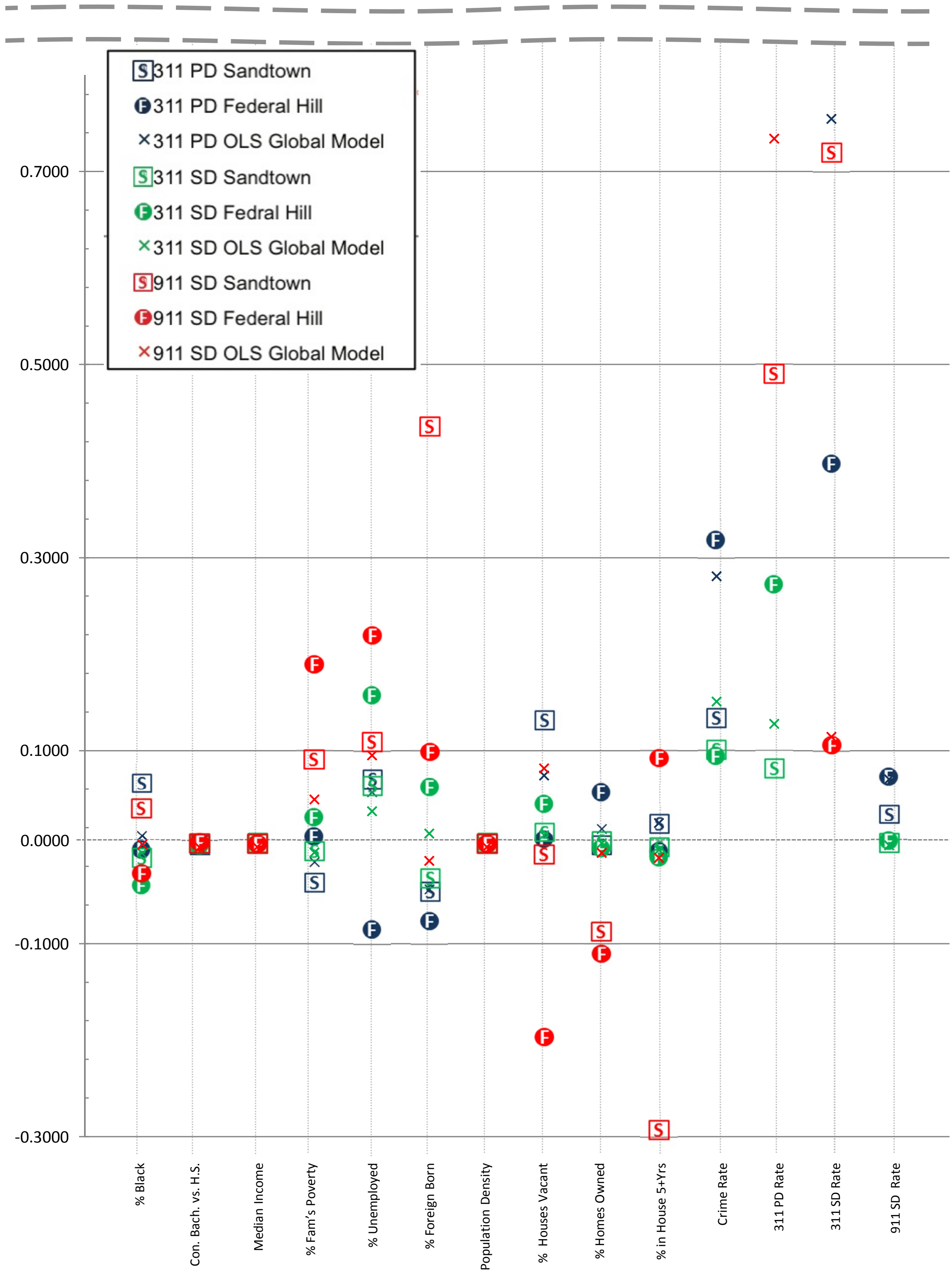


Figure 39 - Compared Global (OLS) and Local (GWR) Coefficient Values for Model Variables For All Predictive Call Rate Models: Sandtown vs. Federal Hill Neighborhood Clusters

changes for ‘Physical Disorder Calls’ than it is able to predict shifts in the rate for ‘Emergency Social Disorder Calls’.

Looking for neighborhood “site to site” patterns I discovered variables that displayed little difference in reported coefficient values from model to model. In particular, a lack of divergence exists between the coefficients generated from the GWR statistics for the dependent variables ‘Percent Black’, ‘Percent of Homes Owned’, ‘Percent of Families in Poverty’ and ‘911 Emergency Social Disorder’ call rate. Unlike the variables noted earlier that display almost “zero” impact coefficients (education, income, and population density) each of these variables has *some* range of coefficient values predicting call rate changes. However, these ranges are minimal compared to the others. Yet, the important observation here is how these variables display a degree of uniformity not only in *each call prediction model* but also at *each* neighborhood site, suggesting the variables are not, particularly, locally-determined or bounded – i.e. their values are not spatially affected.

charts the most divergent independent variable coefficients as well. The variables ‘Unemployed’, ‘Percent Foreign Born’, ‘Percent Houses Vacant’, ‘Percent Lived Home Less than 5 Years’, ‘Crime Rate’(reported Part 1 FBI Crimes), ‘Social Disorder Calls’(rate) and ‘Physical Disorder Calls’ (rate) all show wide to extreme divergence between models *and* between neighborhood sites. ‘Percent Unemployed’ predicts larger increases in call rates for physical and social disorder issues in Federal Hill than in Sandtown – almost three times as much. Though not particularly strong, the same variable predicts a *decrease* in calling rates when predicting ‘Emergency Social Disorder’ calls in the same neighborhood. In Sandtown this variable has little predictive power for any of the three call rate models. ‘Percent Foreign Born’ varies, and specifically in direction of coefficient, for both neighborhoods. In the Sandtown cluster it is highly predictive of positive call rate increases about ‘Emergency Social Disorder’ – for every 2% increase in ‘Percent Foreign Born’ it predicts a 1% in those call rates. It is mildly suppressive in its prediction of call rates for ‘Physical’ and ‘Social Disorder’. The same bifurcation of direction exists for predictions of this variable’s impact in Federal Hill calling patterns – it predicts increases in ‘Emergency Social Disorder Calls’ while it predicts decreases in ‘Physical Disorder Calls’ as ‘Percent Foreign Born’ increases there.

The presence of ‘Vacant Homes’ affects call rates in the two neighborhood sites quite differently. On the one hand the variable predicts increases in call rates for ‘Physical Disorder’ as ‘Percent Vacant Houses” increases in Sandtown, but no effect in Federal Hill. Oddly, in Federal Hill increases in vacant homes predict a *decrease* in calls for ‘Emergency Social Disorder’. This is also only one of two variables that appear to suppress call rates for ‘Emergency Social Disorder’ in Federal Hill. The other variable was ‘Percent of Homes Owned’. Above I noted the substantially different, in power and direction, coefficients for the variable “Lived in Home Less than 5 Years” when predicting ‘Emergency Social Disorder’ (positive for Federal Hill, negative for Sandtown) and only add here that all other models show little to no explanatory power for this same variable.

Viewing differences in the call rate variables, and their impacts on other rates, we can see residents in Sandtown actively calling about “social disorder’ coincides with a predicted increase of about 3% to the call rate for issues concerning ‘311 Physical

Disorder'. Yet, this same variable exerts far less influence in Federal Hill. There its coefficient is reported as 0.394 versus a coefficient of 2.88 in Sandtown. Sandtown residents' increase in calls about physical disorder issues increases seven fold, for every one-unit increase in social disorder problems, compared to Federal Hill's rate. Further, while '311 Calls for Social Disorder' were expected to fuel calls for *emergency* social disorder they predicted larger increases in call rate change for the '*Physical* Disorder Calls' model than for the 'Emergency Social Disorder' calls prediction model.

There also appears to be local patterns of magnitudes of effects on call rates within the neighborhoods. When predicting rate change within a model some variables report different values from site to site. When comparing models *within a variable* coefficients from *both* models appear to vary in similar magnitudes. For example, consider the independent variable '311 Social Disorder Call Rate'. On the chart are plotted four values – the Sandtown coefficient predicting 'Physical Disorder' rate change, followed by the Sandtown coefficient predicting 'Emergency Social Disorder' call rate change, then the Federal Hill value for 'Physical Disorder', followed by the Federal Hill coefficient predicting change in 'Emergency Social Disorder' call rates. Sandtown, Sandtown, Federal Hill, and then Federal Hill. Testing the magnitude of differences we find the first coefficient from Sandtown to be 2.88, the next, again from is Sandtown, predicting increases in 'Emergency Social Disorder Calls' is measured as 0.72. The two following coefficients come from Federal Hill, first predicting change in 'Physical Disorder Calls' by a coefficient of 0.39, and then the predictive coefficient for 'Emergency Social Disorder Calls' with a value of 0.10. in the first case the magnitude of difference between the coefficients of prediction for rate changes for “Emergency Social Disorder” (by the ‘311 Social Disorder Call Rate’) is roughly 7.4 times greater in Sandtown compared to Federal Hill. When mapping the second relationship, predicting changes in ‘Physical Disorder Calls’, the difference between the two site values is a 7.00 times greater strength again in Sandtown versus Federal Hill. In both cases, for one variable, for two different models, the magnitude of difference is similar, and at the *same site – Sandtown*. This same kind of magnitude pattern appears to also hold for the model input variable ‘311 Physical Disorder’. Here, predicting ‘Emergency Social Disorder’ and ‘Social Disorder’ call rate changes with this variable we find magnitude differences of 2.65 times more powerful (when predicting changes in emergency social disorder call rates) and 3.30 times more powerful (when predicting changes in social disorder call rates) for the *Federal Hill site* this time, compared to results from Sandtown. It is not clear but we may be seeing how sites shape predictor coefficients to some degree.

Turning to coefficients for the independent variables that display the widest range, across models and between neighborhood sites extreme results are for the variable ‘Crime Rate’. On the lower end of the spectrum it produced coefficients predicting a one unit increase in the rate of calls about ‘Social Disorder’ for every 10 unit increase in ‘Crime Rate’ in both neighborhoods. At the other extreme, when projecting outcomes for “Emergency Social Disorder Calls”, the variable “Crime Rate” produced predictive coefficients of 6.77 in Sandtown and 2.29 in Federal Hill. This represented a three fold difference in power between the two sites. Accordingly a 1% increase in crime in Sandtown generates a 6.8% increase in calls to remediate ‘911 Emergency Social Disorder’ whereas in Federal Hill that same increase in violent crime only generates a 2.3% increase in calling behavior. “Crime rate” then has very different effects on an otherwise seemingly simple behavior – picking up the telephone and making a call about a neighborhood problem. This illustrates that perceptions of “social disorder”, and then taking action about a behavior, might be similar at both sites. However, “emergency social disorder” perceptions might be *different* at both neighborhood sites (what will or will not be attended to bothersome, offensive) and how those perceptions translate into different calling behaviors or patterns, between the two different sites.

Mapped Call Rates and Measures of LISA Tests (Local Indicators of Spatial Autocorrelation) Calls for Services Variables

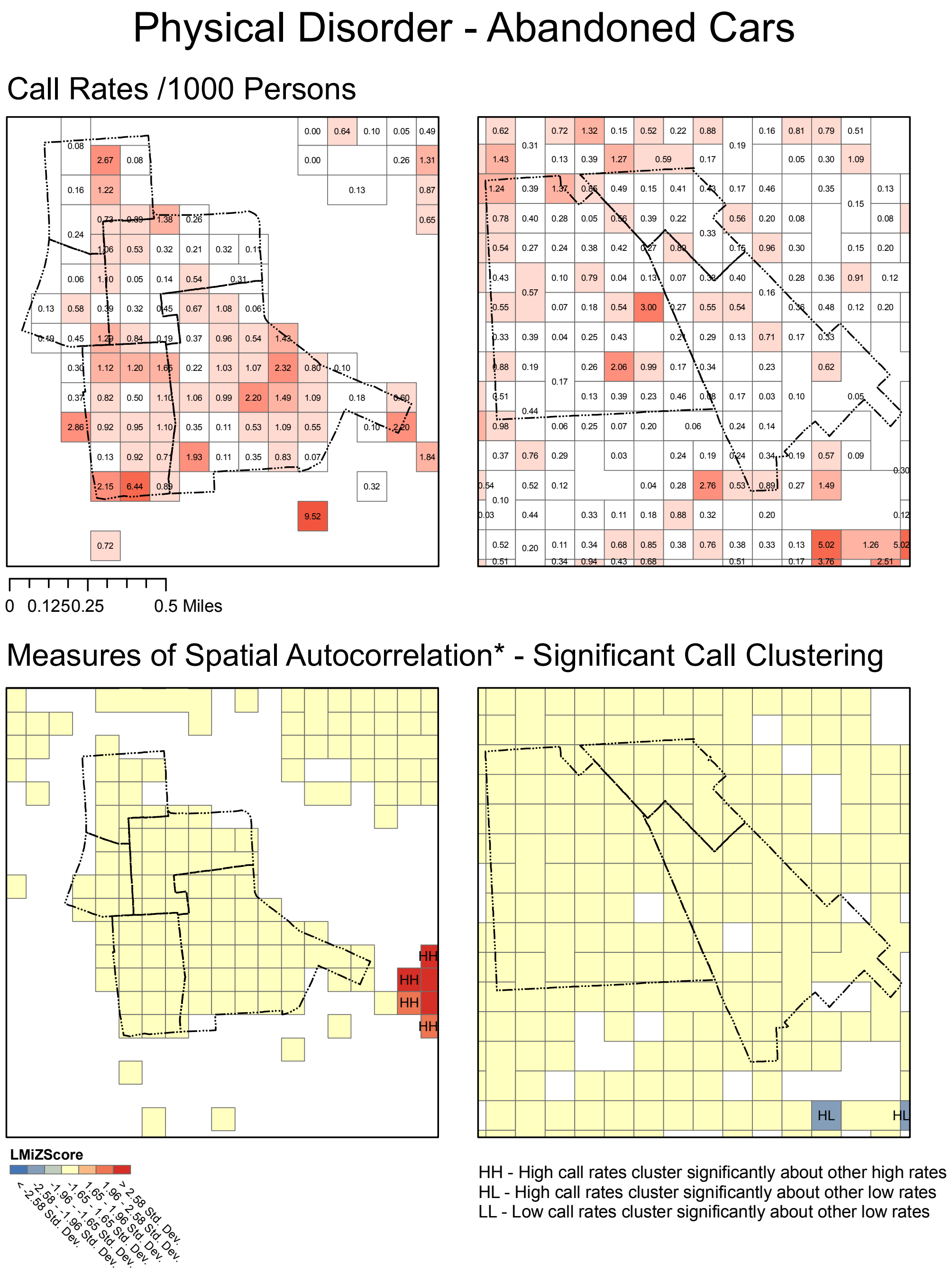


Figure 40 – 311 Calls for Physical Disorder – Abandoned Cars

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

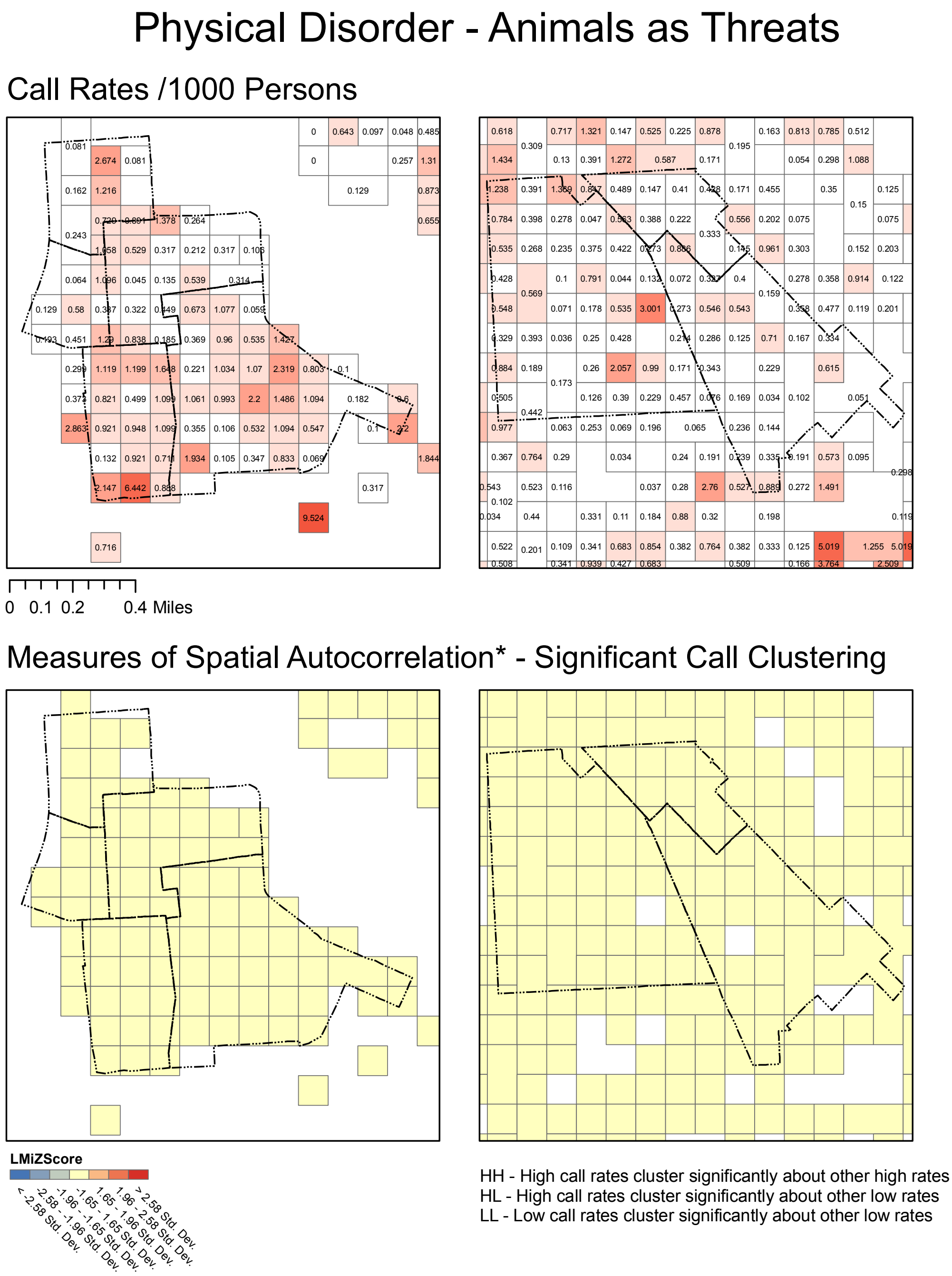


Figure 41 – 311 Calls for Physical Disorder – Animals as Threats

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

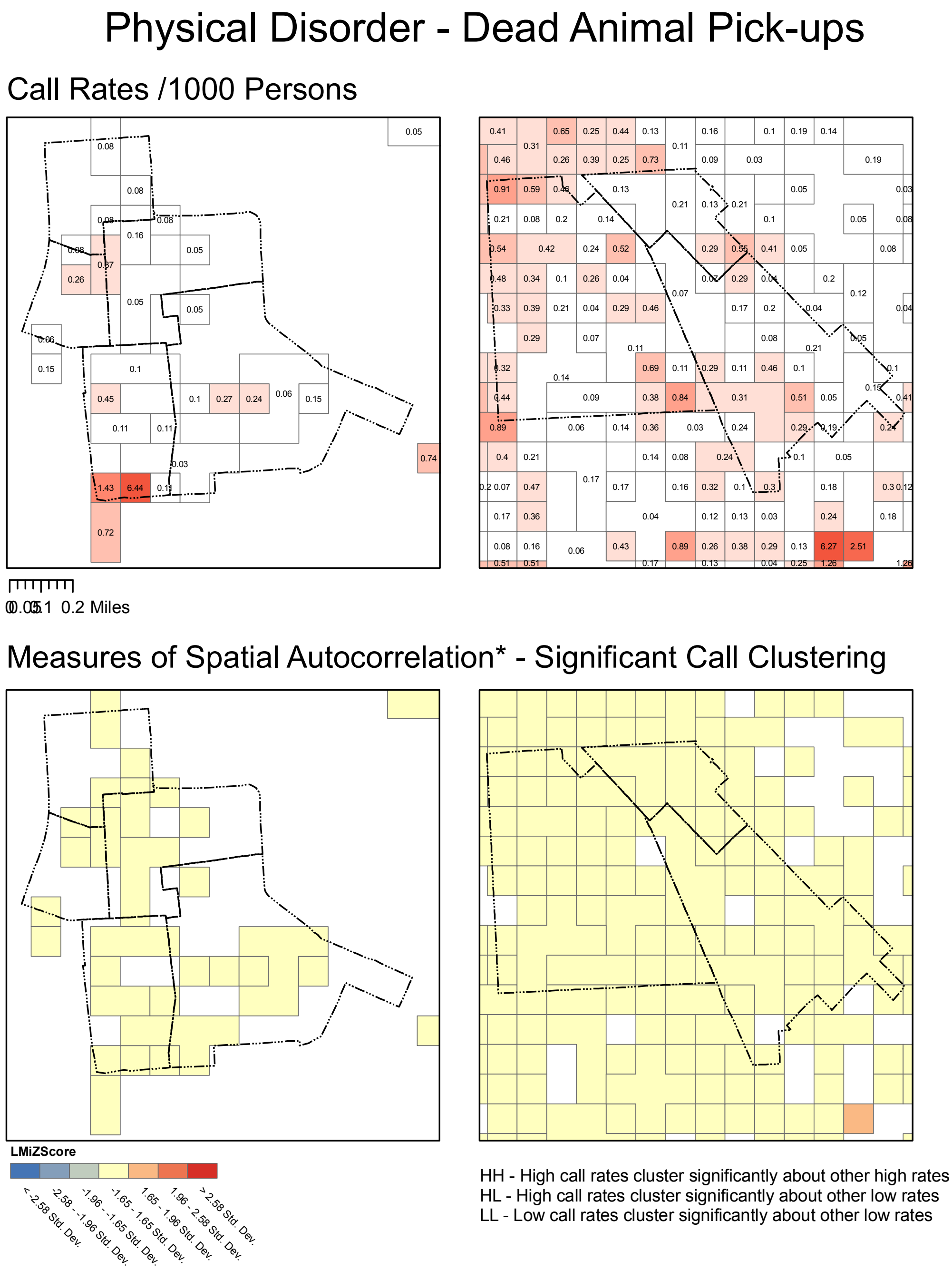


Figure 42 - 311 Calls for Physical Disorder – Dead Animal Pickup Requests

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

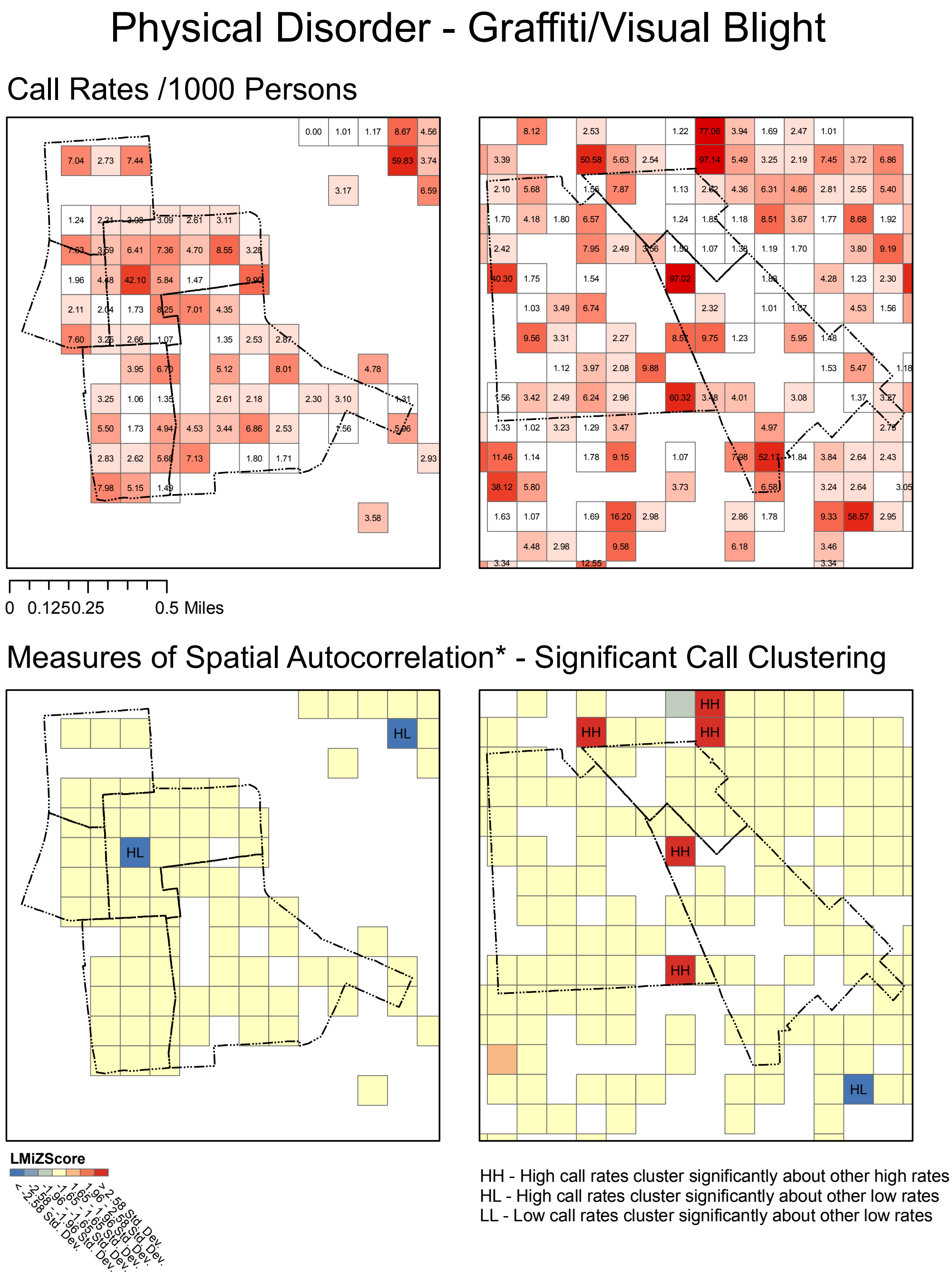


Figure 43 - 311 Calls for Physical Disorder – Graffiti and Visual Blight Calls

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

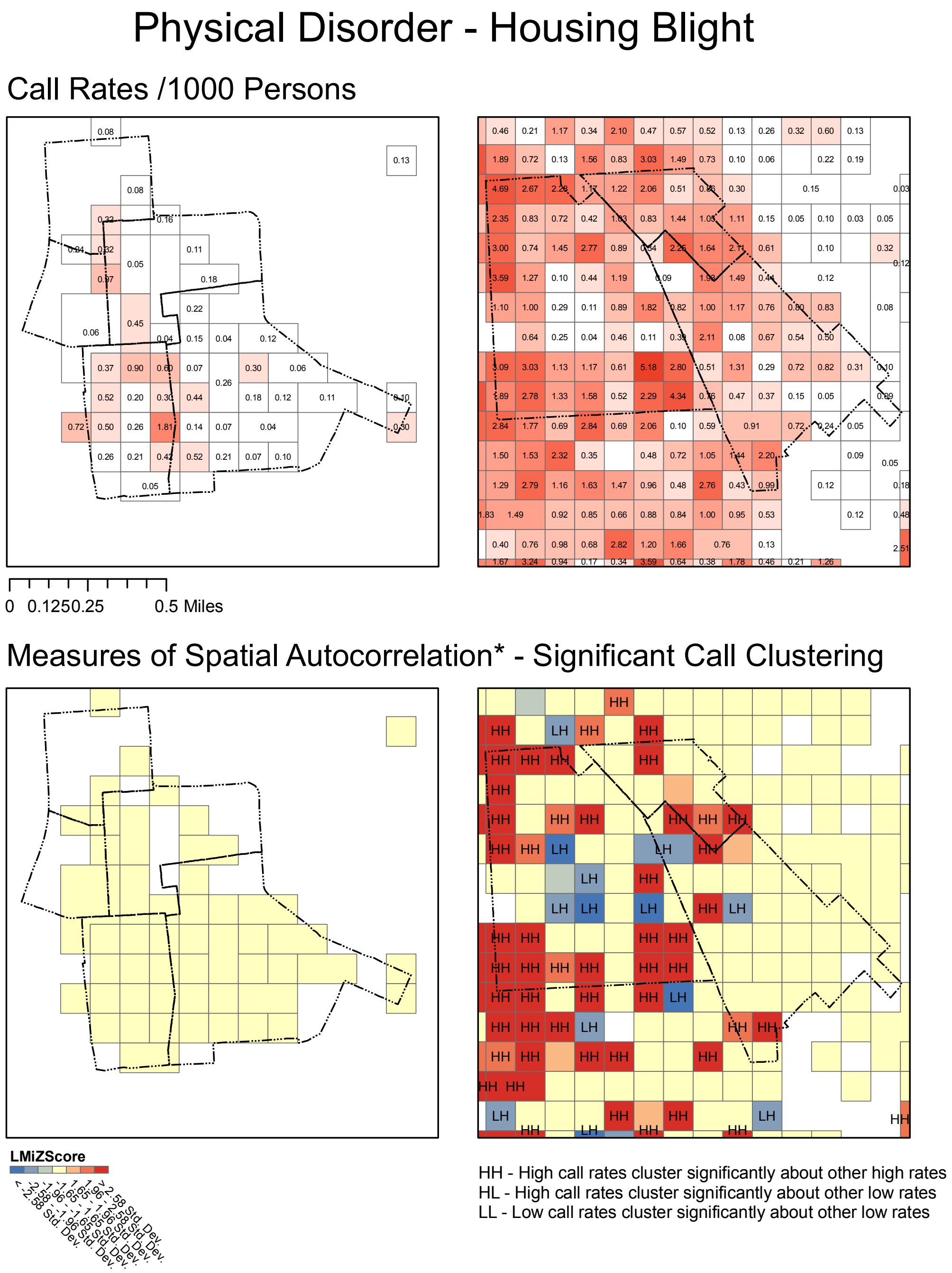


Figure 44 - 311 Calls for Physical Disorder – Housing Blight

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

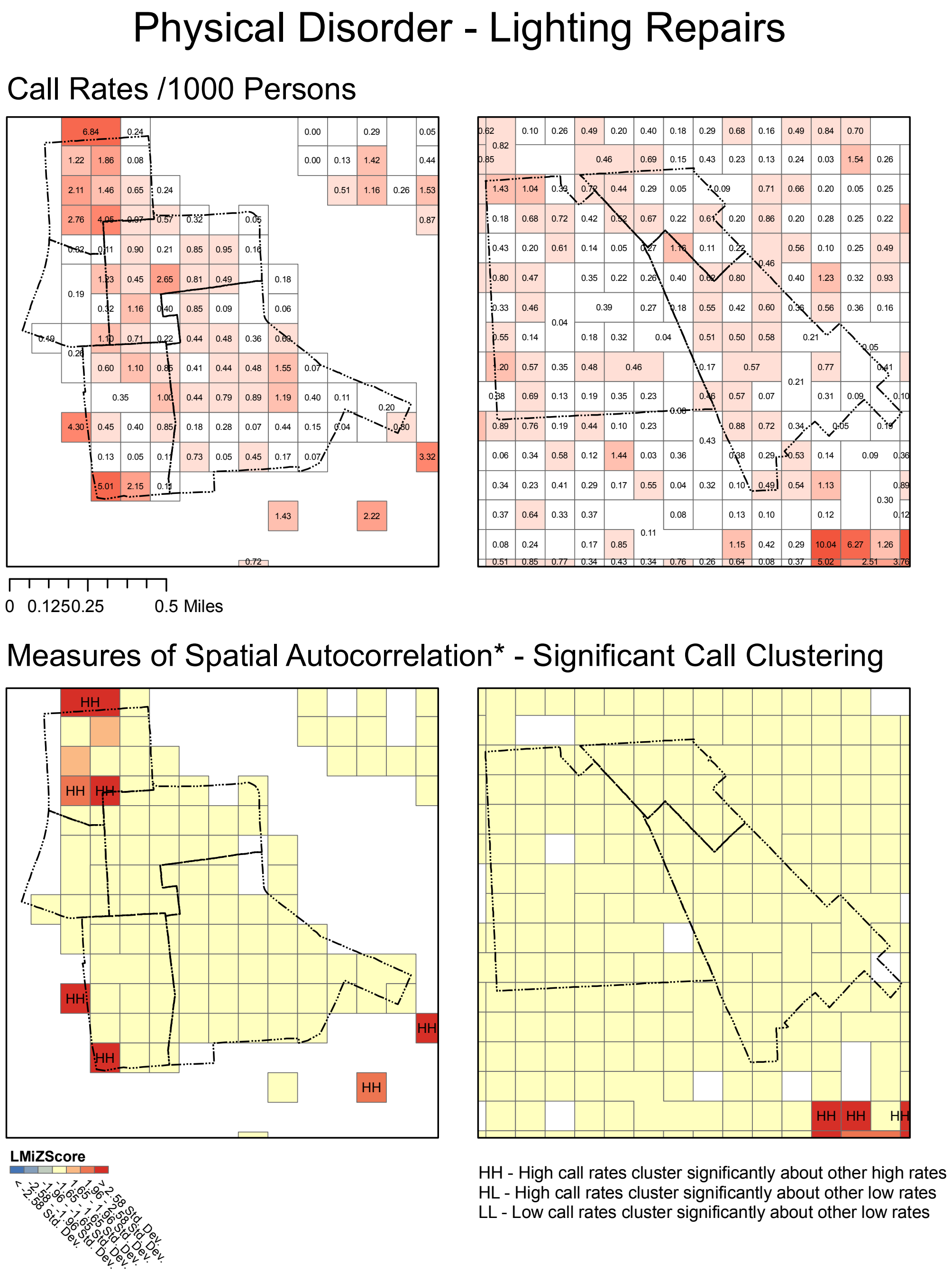


Figure 45 - 311 Calls for Physical Disorder – Lighting Repair Requests

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

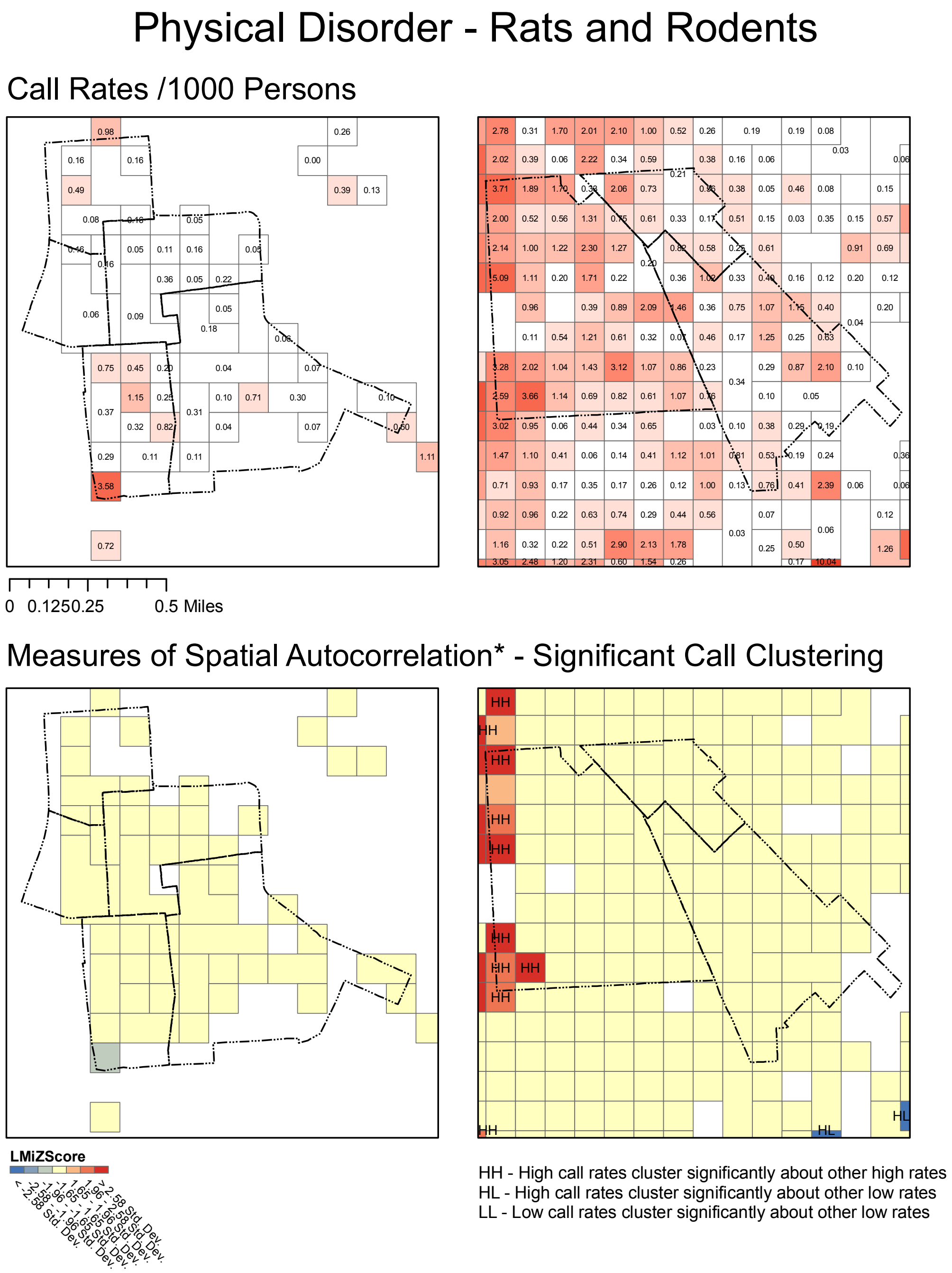


Figure 46 - 311 Calls for Physical Disorder – Rodent Control Requests

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

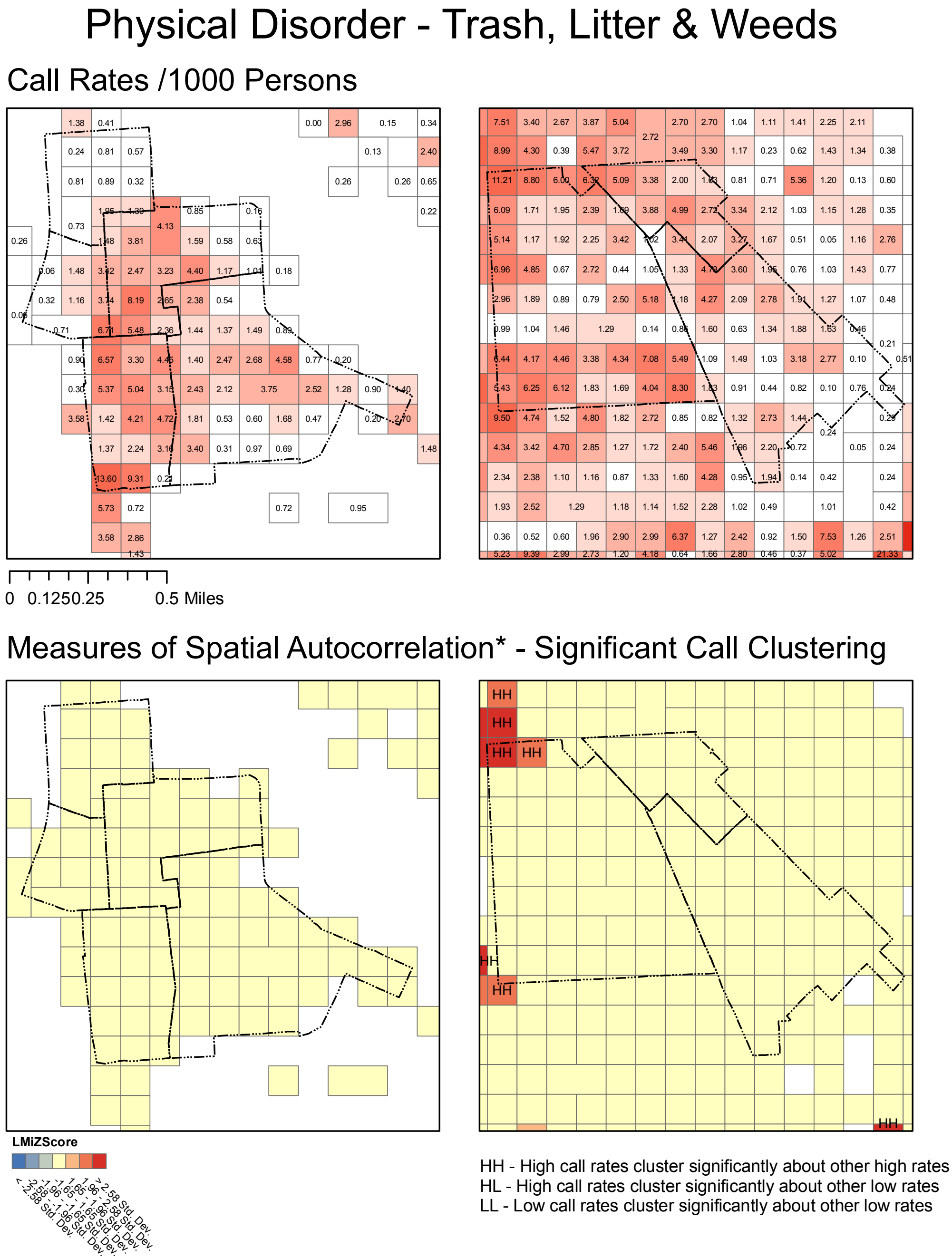


Figure 47 - 311 Calls for Physical Disorder – Calls for Litter, Trash and Weeds/Overgrowth

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

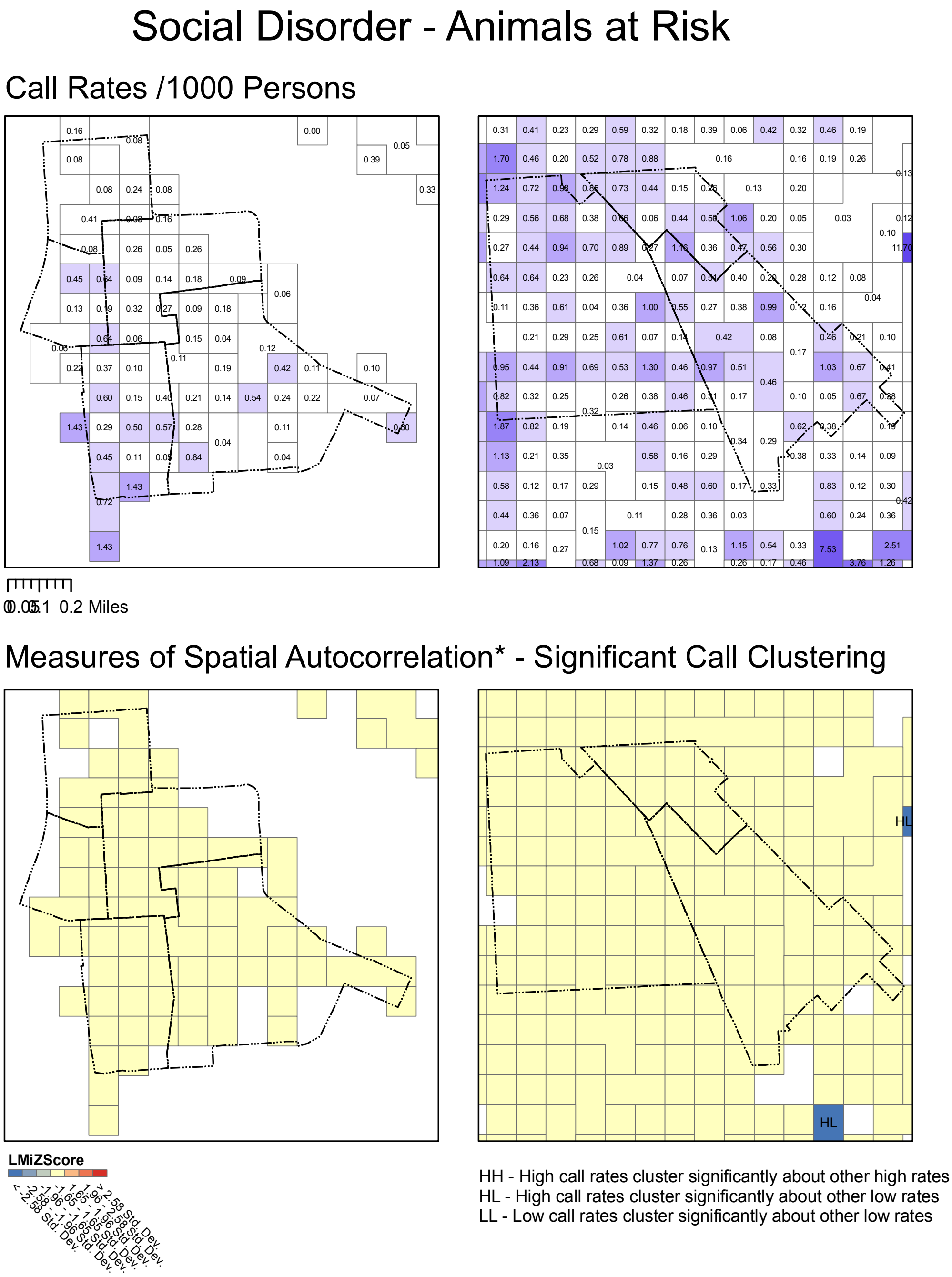


Figure 48 - 311 Calls for Social Disorder – Animals at Risk of Abuse or Harm

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

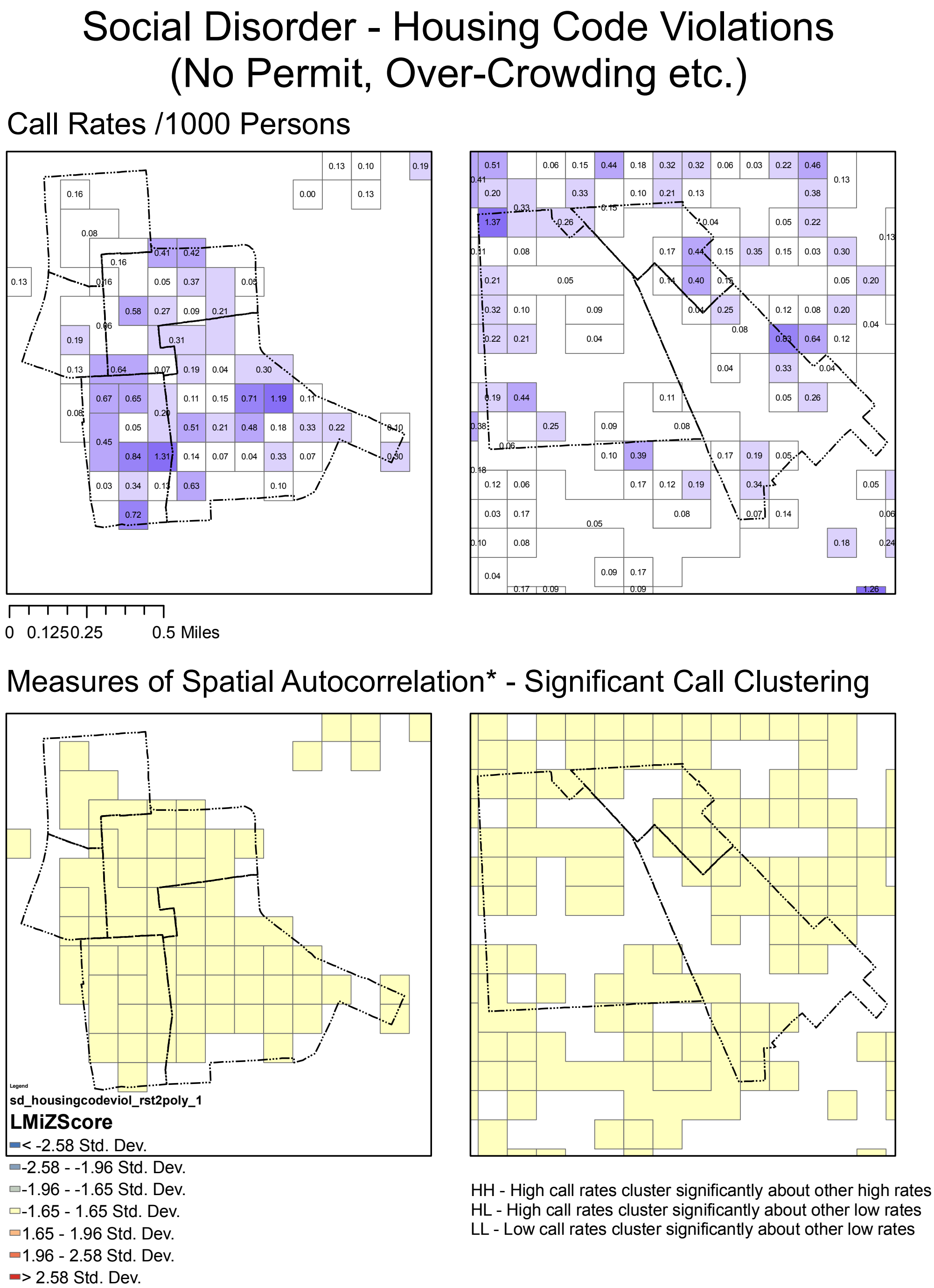


Figure 49 - 311 Calls for Social Disorder – Housing Code Violations

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

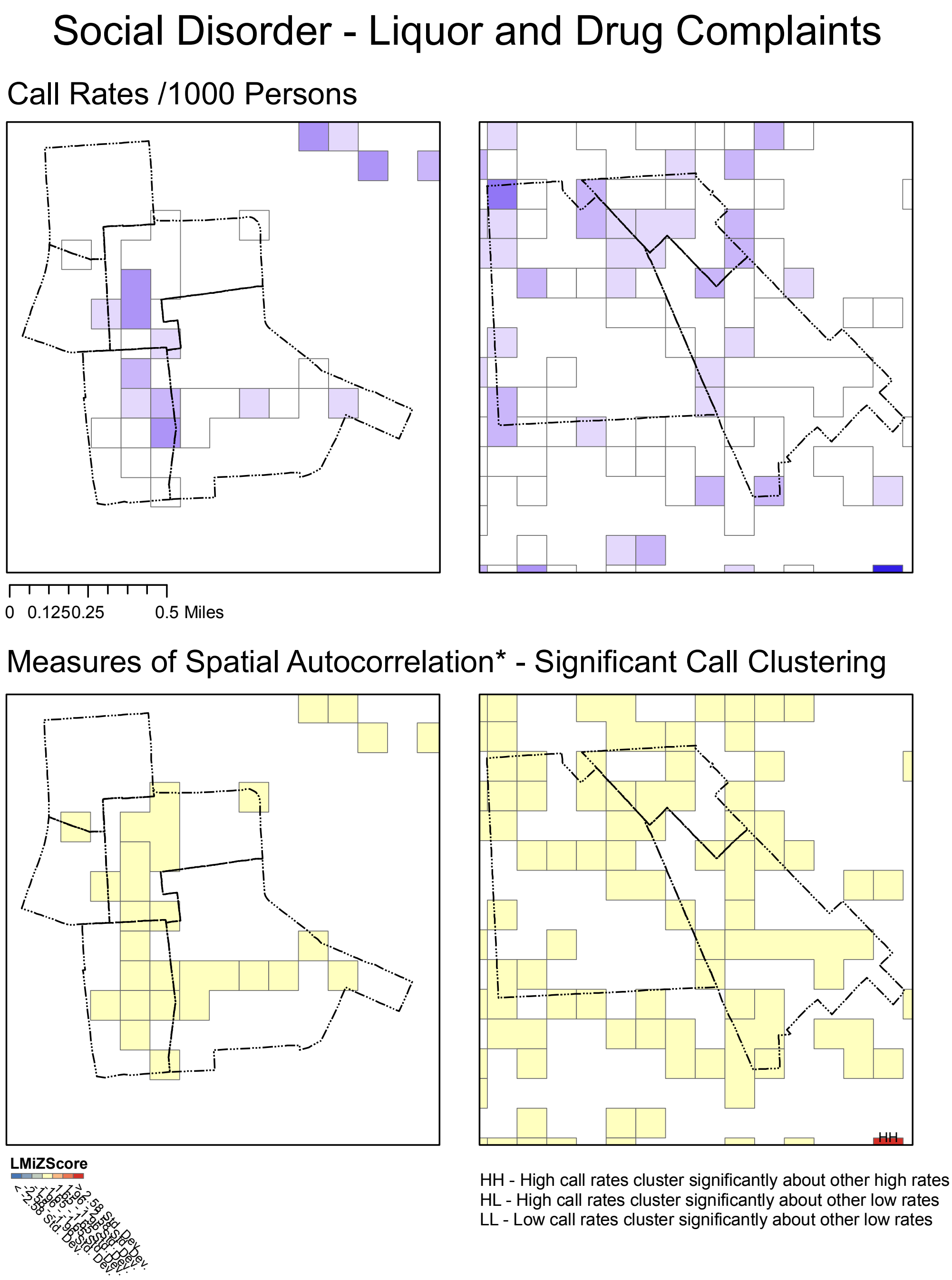


Figure 50 - 311 Calls for Social Disorder – Liquor and Drug Use Complaints

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

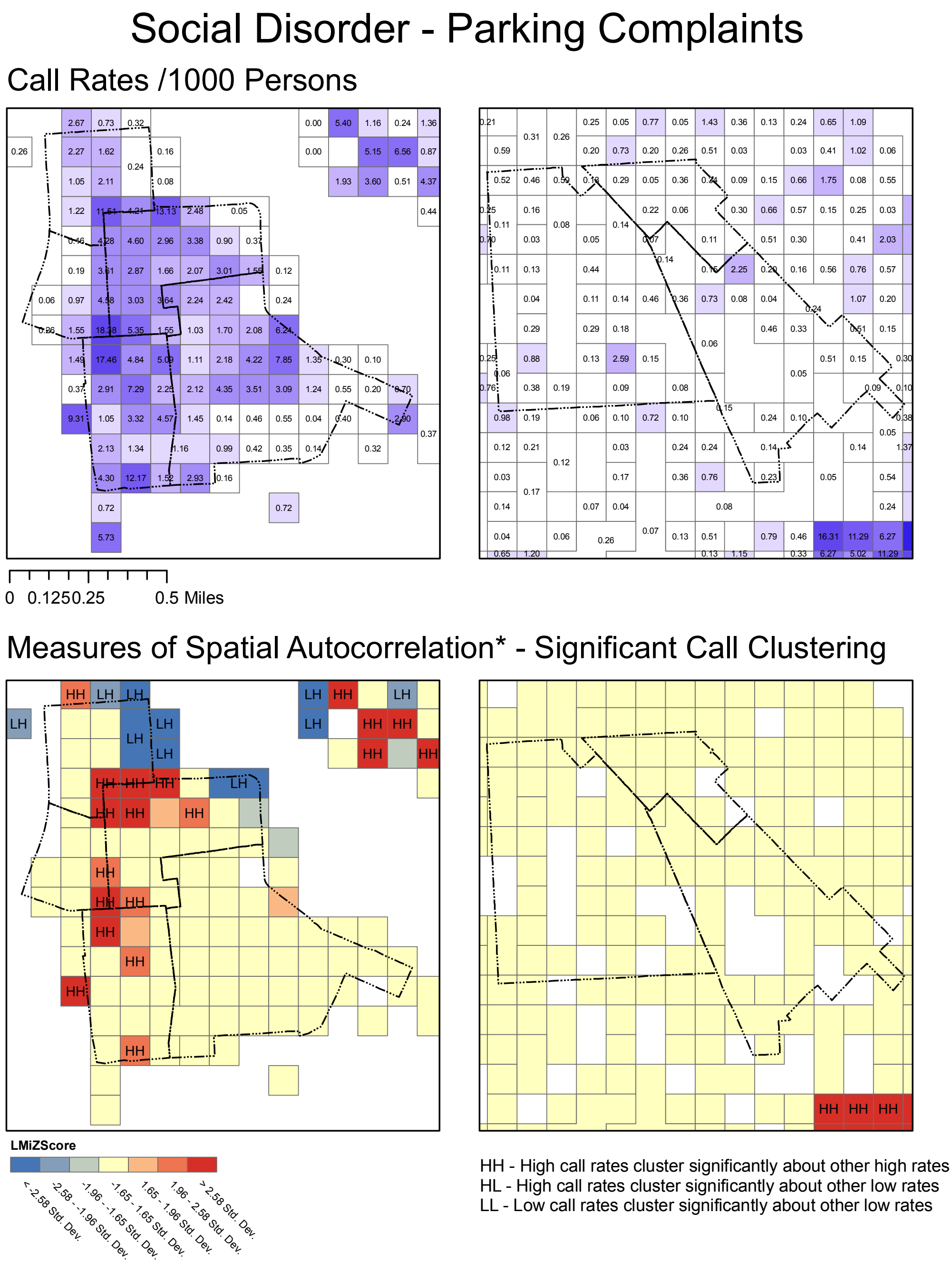


Figure 51 - 311 Calls for Social Disorder – Parking Complaints

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

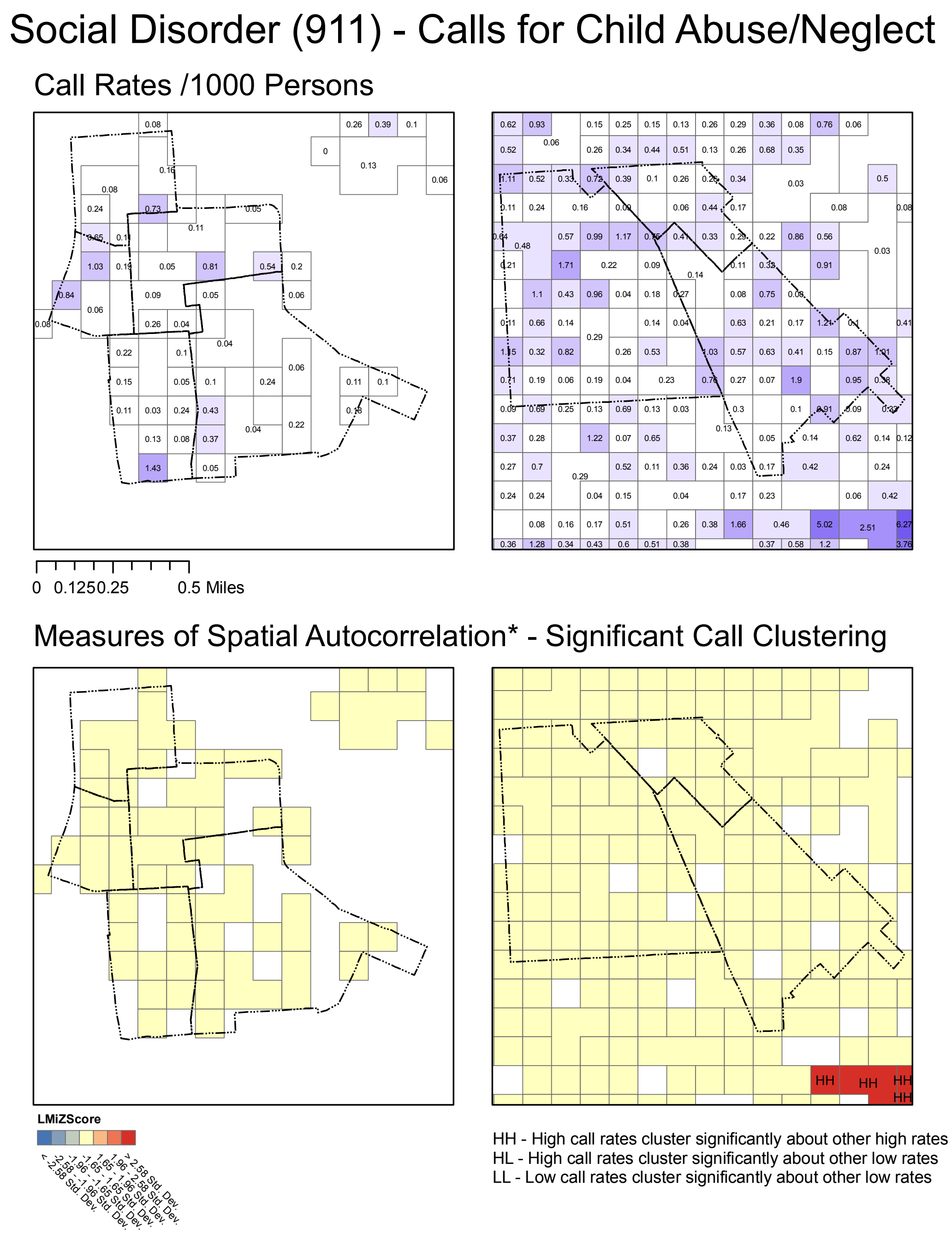


Figure 52 - 311 Calls for Emergency Social Disorder – Calls Concerning Child Abuse or Neglect

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

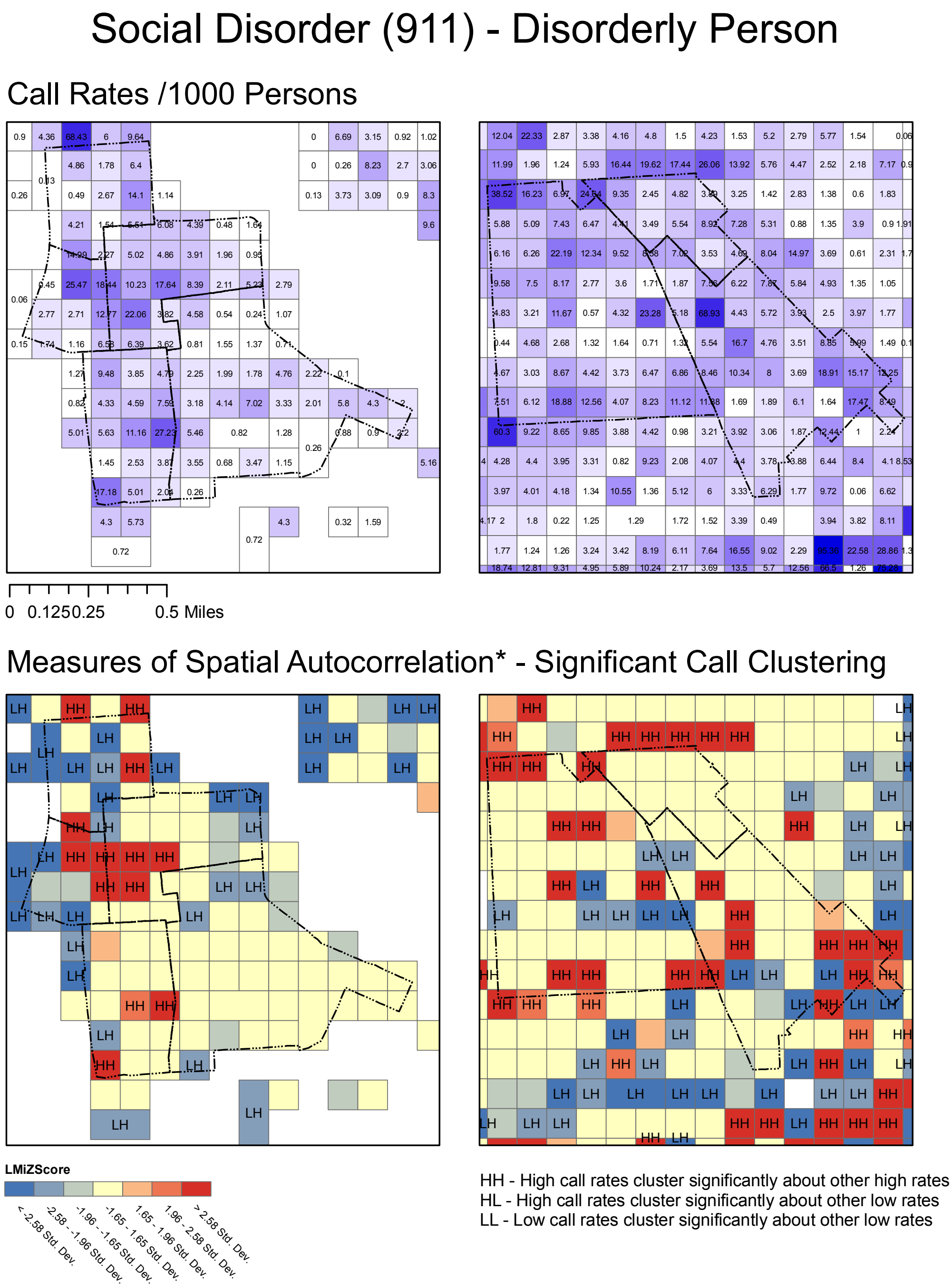


Figure 53 - 311 Calls for Emergency Social Disorder – Disorderly Person

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

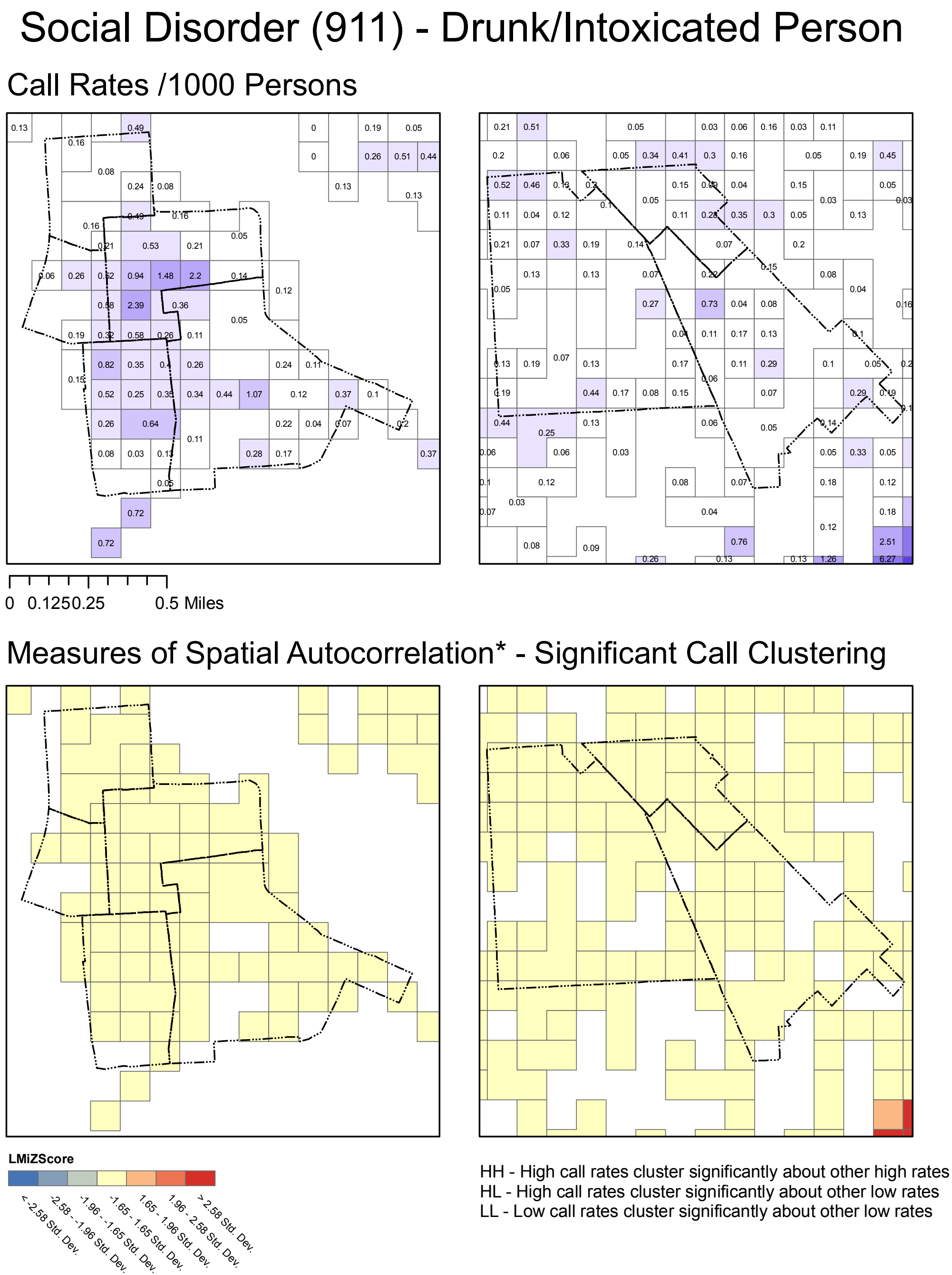


Figure 54 - 311 Calls for Emergency Social Disorder – Drunk or Intoxicated Person Reported

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

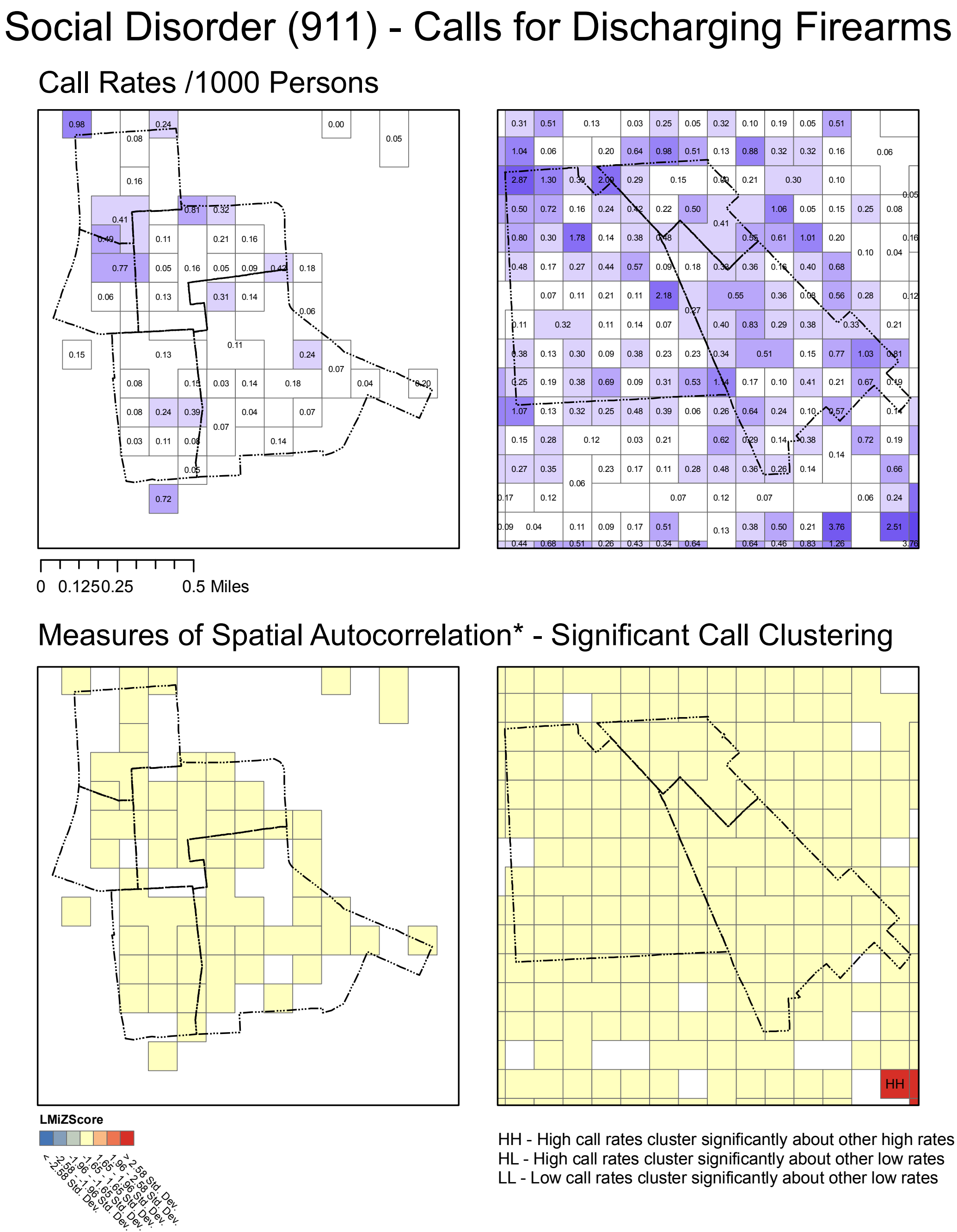


Figure 55 - 311 Calls for Emergency Social Disorder – Calls Reporting Discharge of Firearms

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

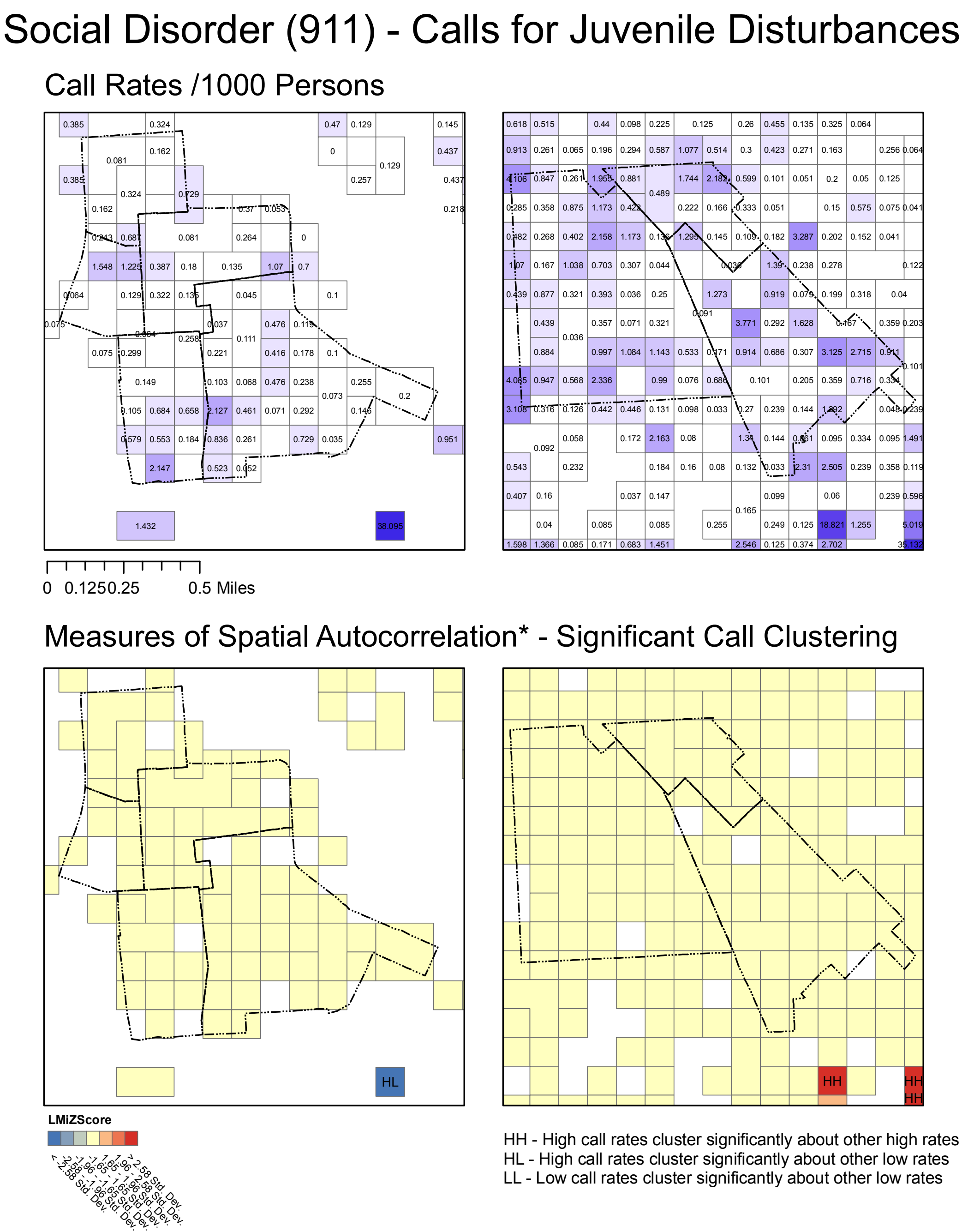


Figure 56 - 311 Calls for Emergency Social Disorder – Calls for Juvenile Disturbance

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

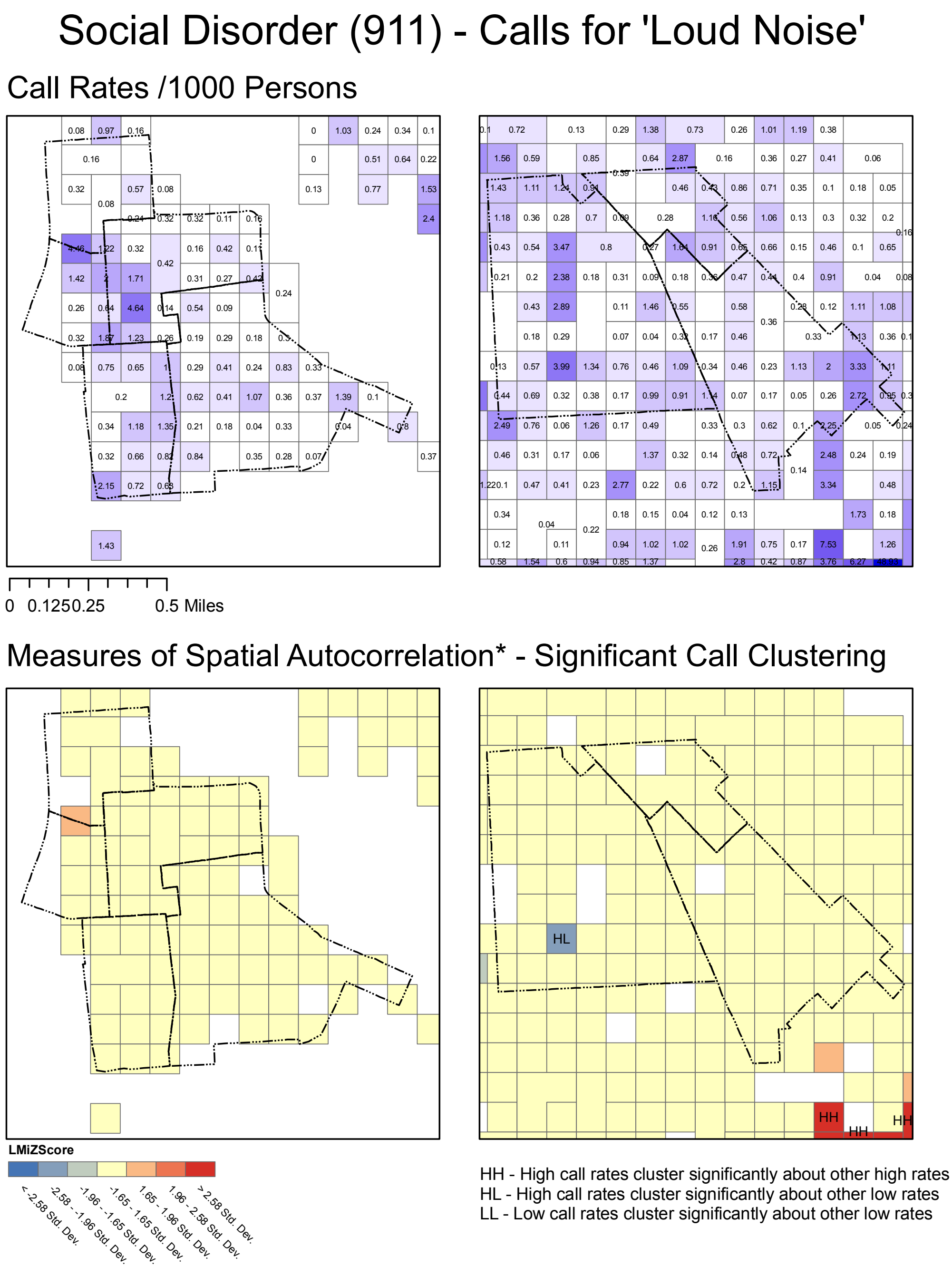


Figure 57 - 311 Calls for Emergency Social Disorder – Calls Reporting Noise Complaints/Loud Noise

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

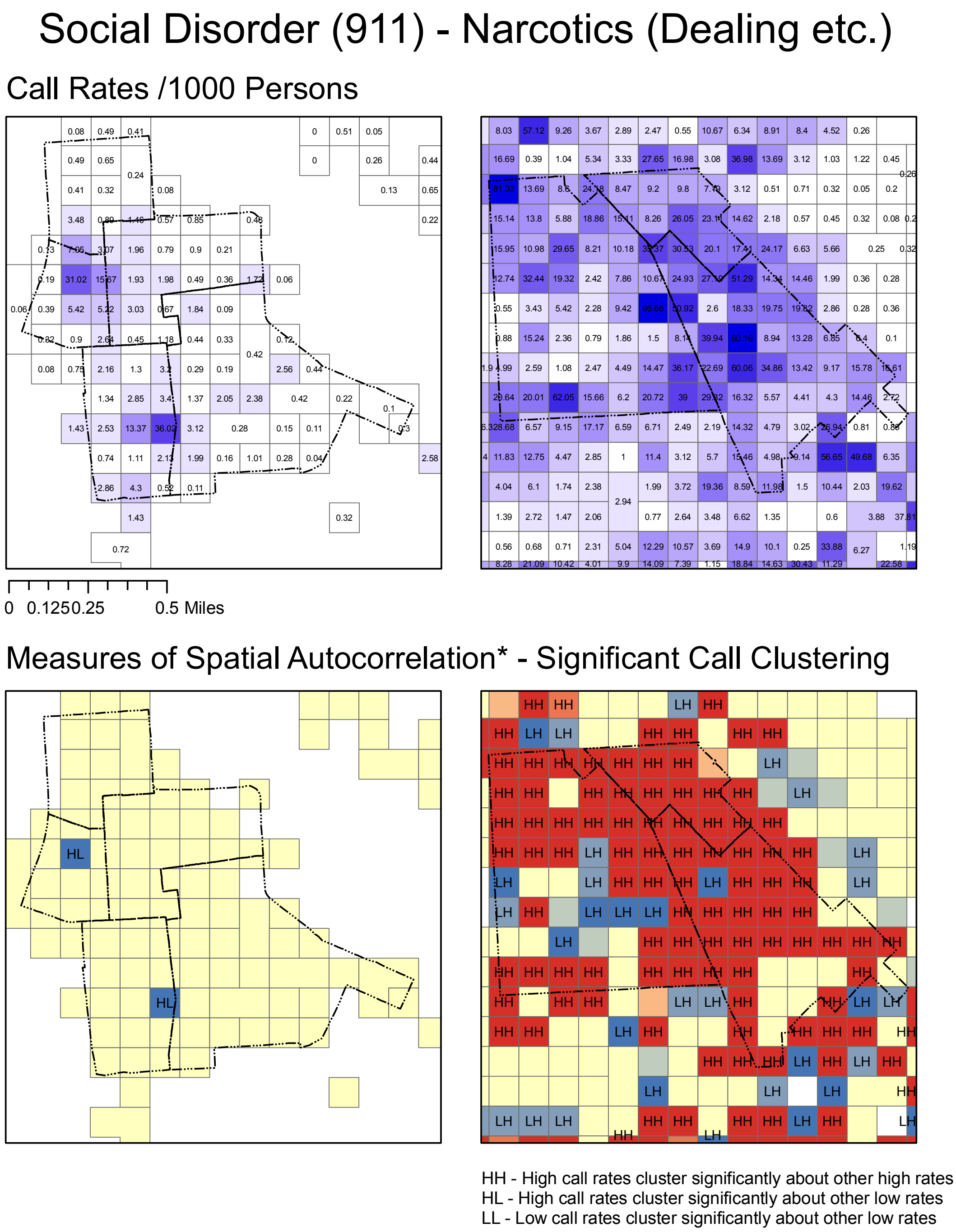


Figure 58 - 311 Calls for Emergency Social Disorder – Calls Reporting Narcotic Use, Dealing etc.

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

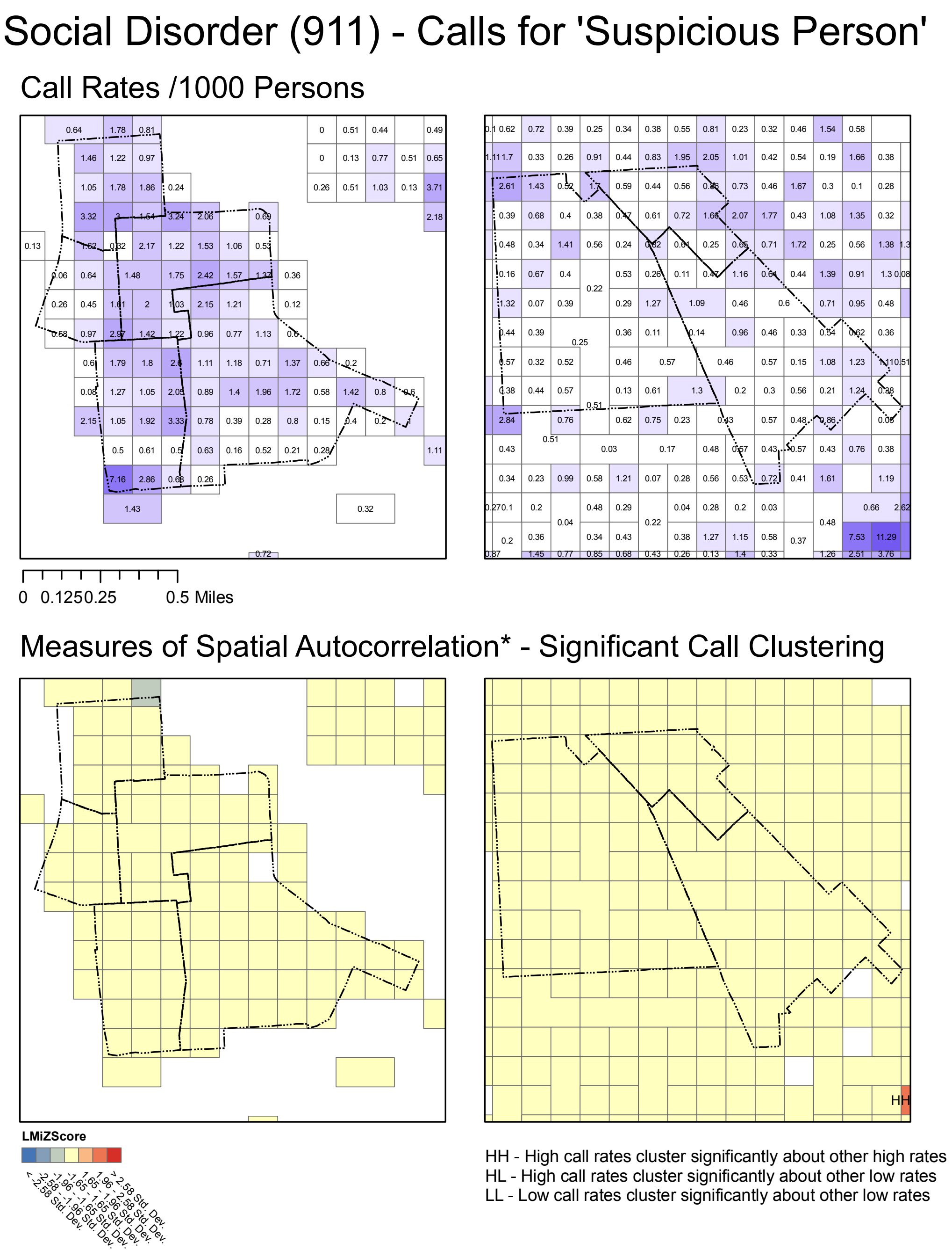
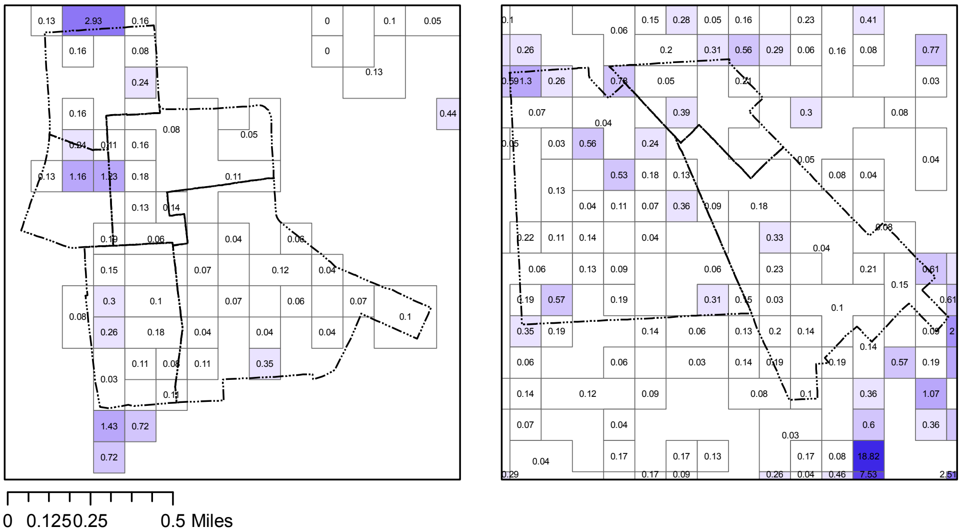


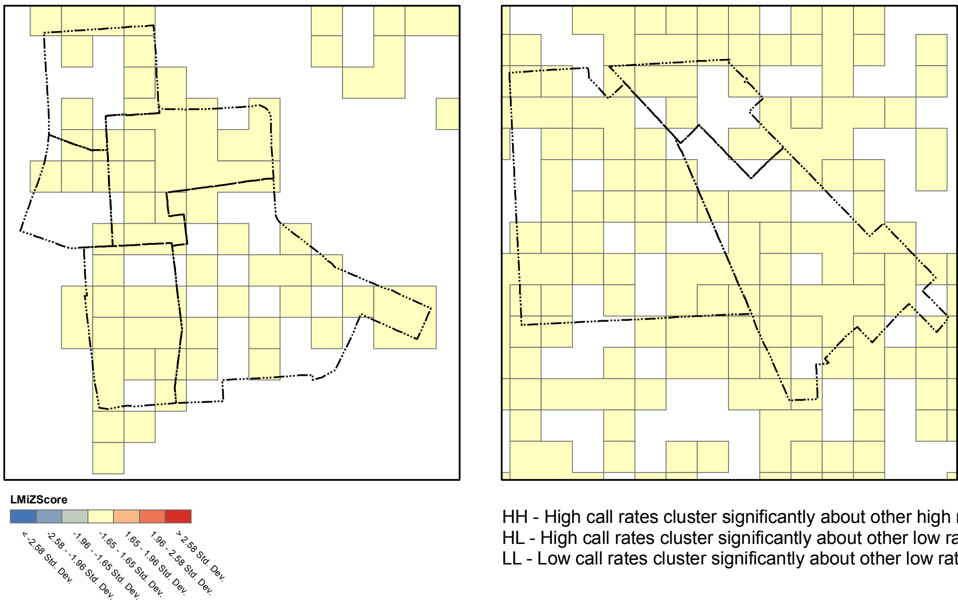
Figure 59 - 311 Calls for Emergency Social Disorder – Calls Reporting a 'Suspicious Person'
Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

Social Disorder (911) - Vehicular Disturbance/'Dirtbikers'

Call Rates /1000 Persons



Measures of Spatial Autocorrelation* - Significant Call Clustering



HH - High call rates cluster significantly about other high rates
HL - High call rates cluster significantly about other low rates
LL - Low call rates cluster significantly about other low rates

Figure 60 - 311 Calls for Emergency Social Disorder – Calls Reporting Vehicular Disturbances

Note: Federal Hill neighborhood cluster to left, Sandtown neighborhood cluster to right.

Geographic Weighted Regression – Maps of Local Variable Coefficients by Model, Both Neighborhoods

In each of the following figures the neighborhood to the north is the Sandtown neighborhoods cluster while to the south is located the Federal Hill neighborhoods cluster.

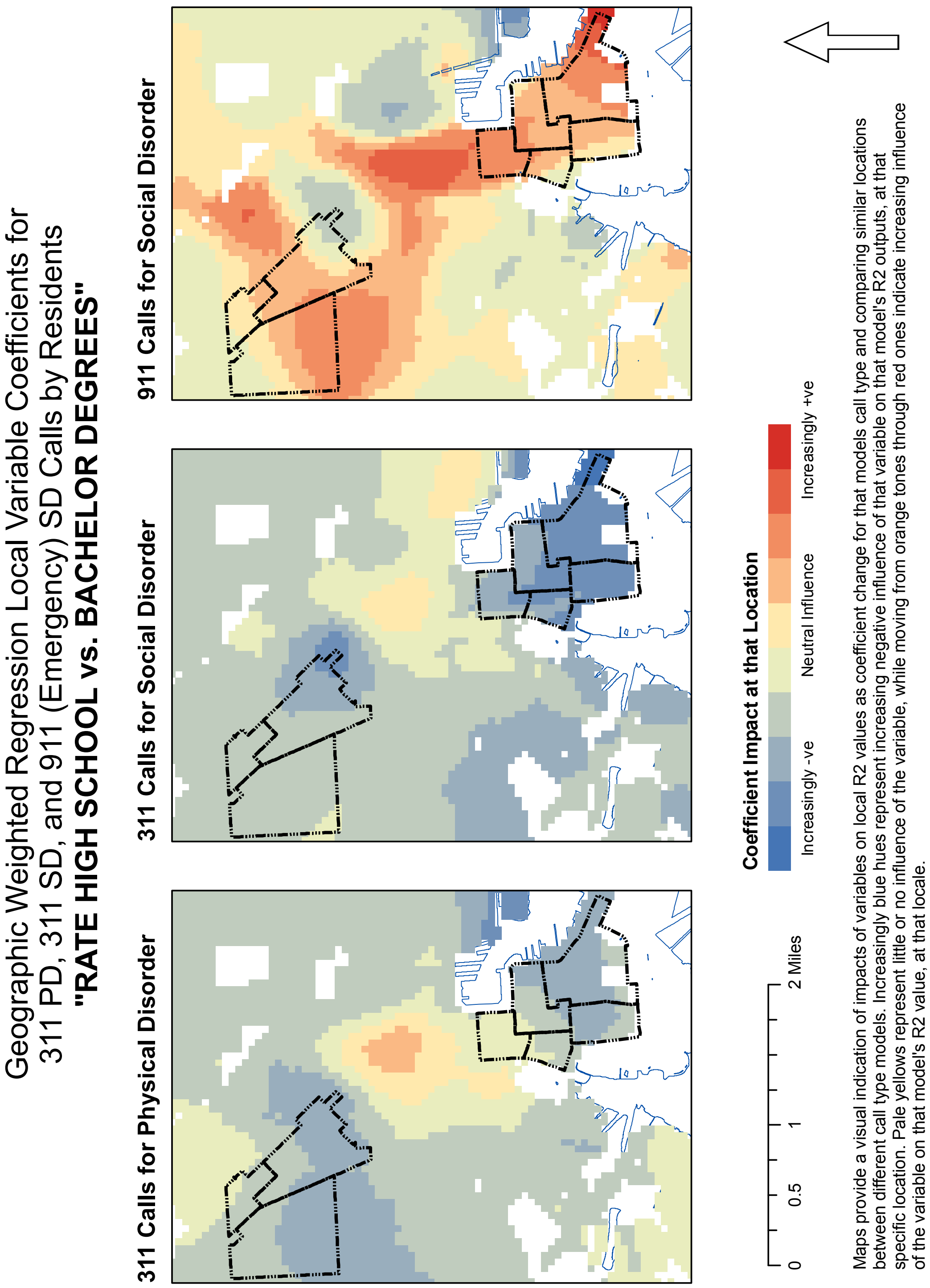


Figure 61 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Rate (proportion) High School vs. Bachelor Degrees (Diplomas)"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

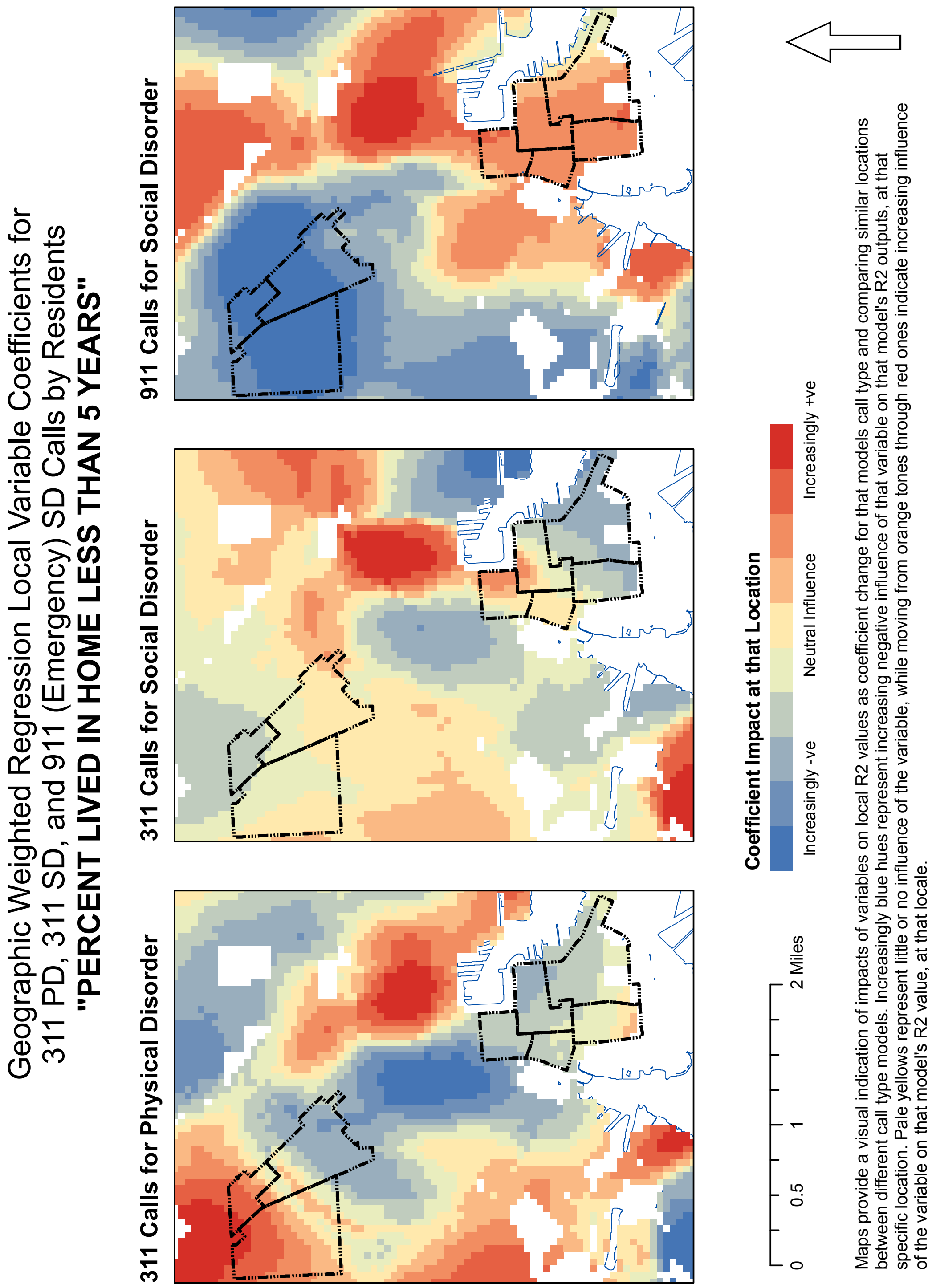


Figure 62 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent Residents Moved in Last Five Years"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

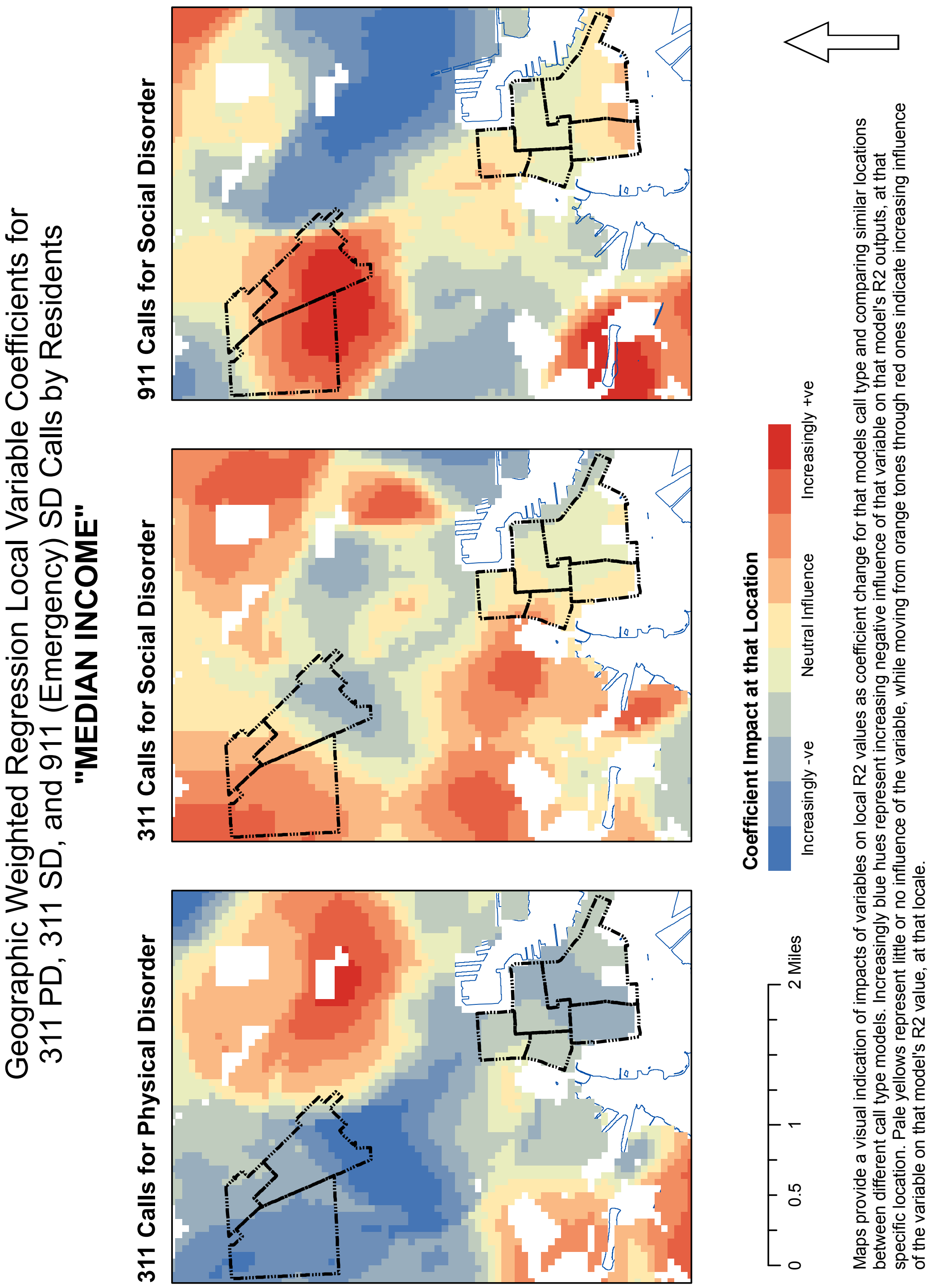


Figure 63 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Median Household Income"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

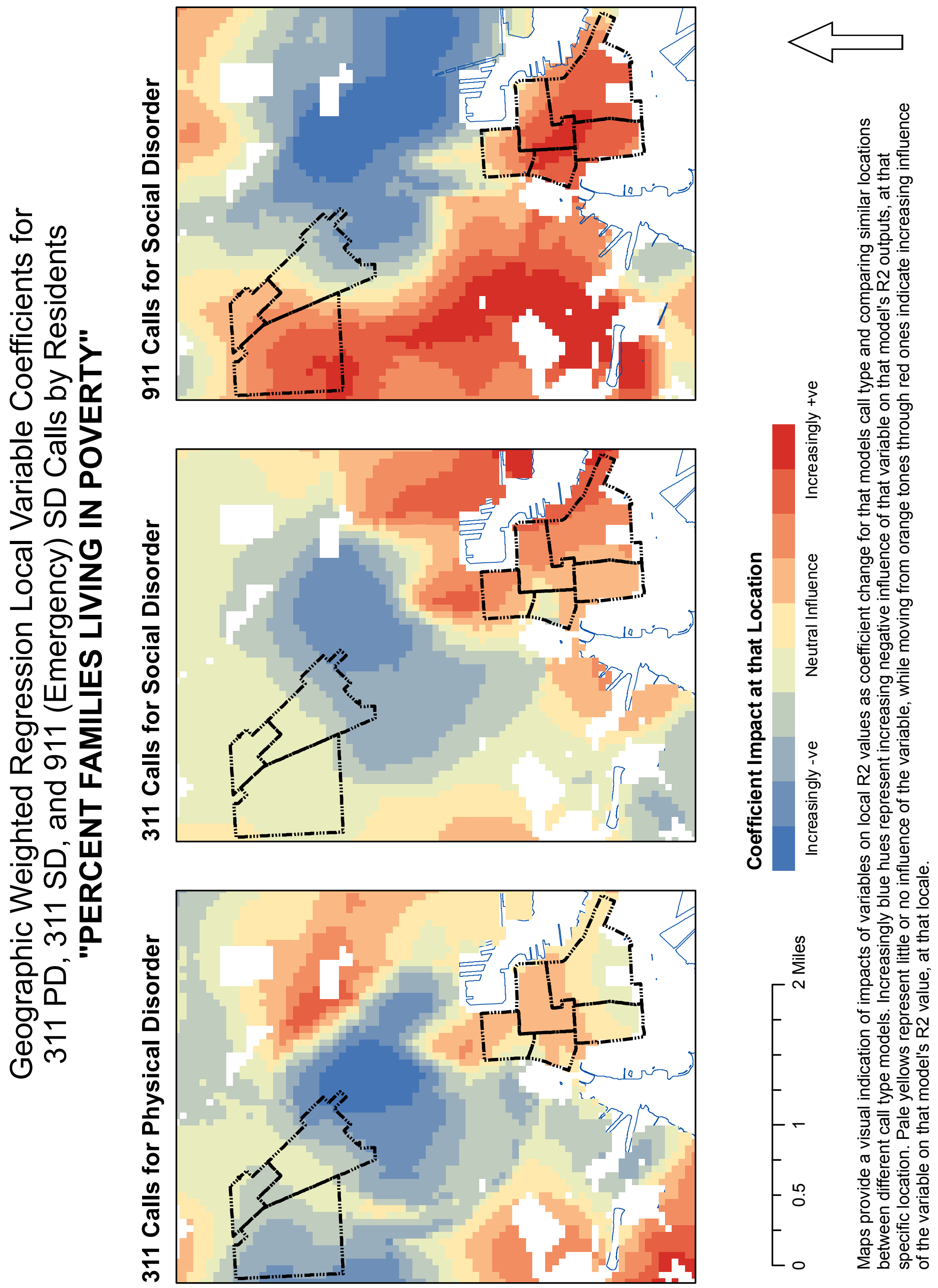


Figure 64 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent of Families Living in Poverty"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

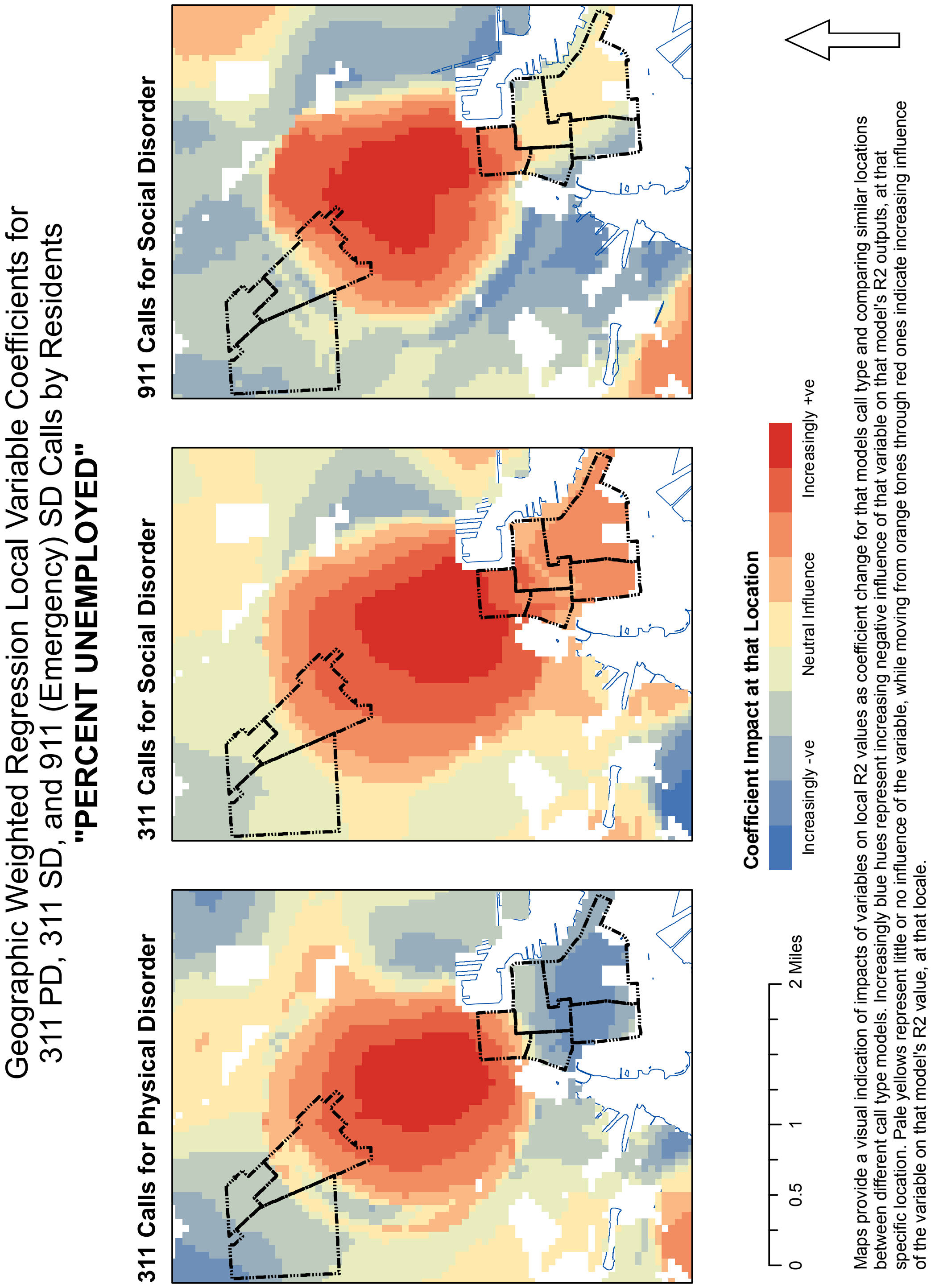


Figure 65 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent Unemployed"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

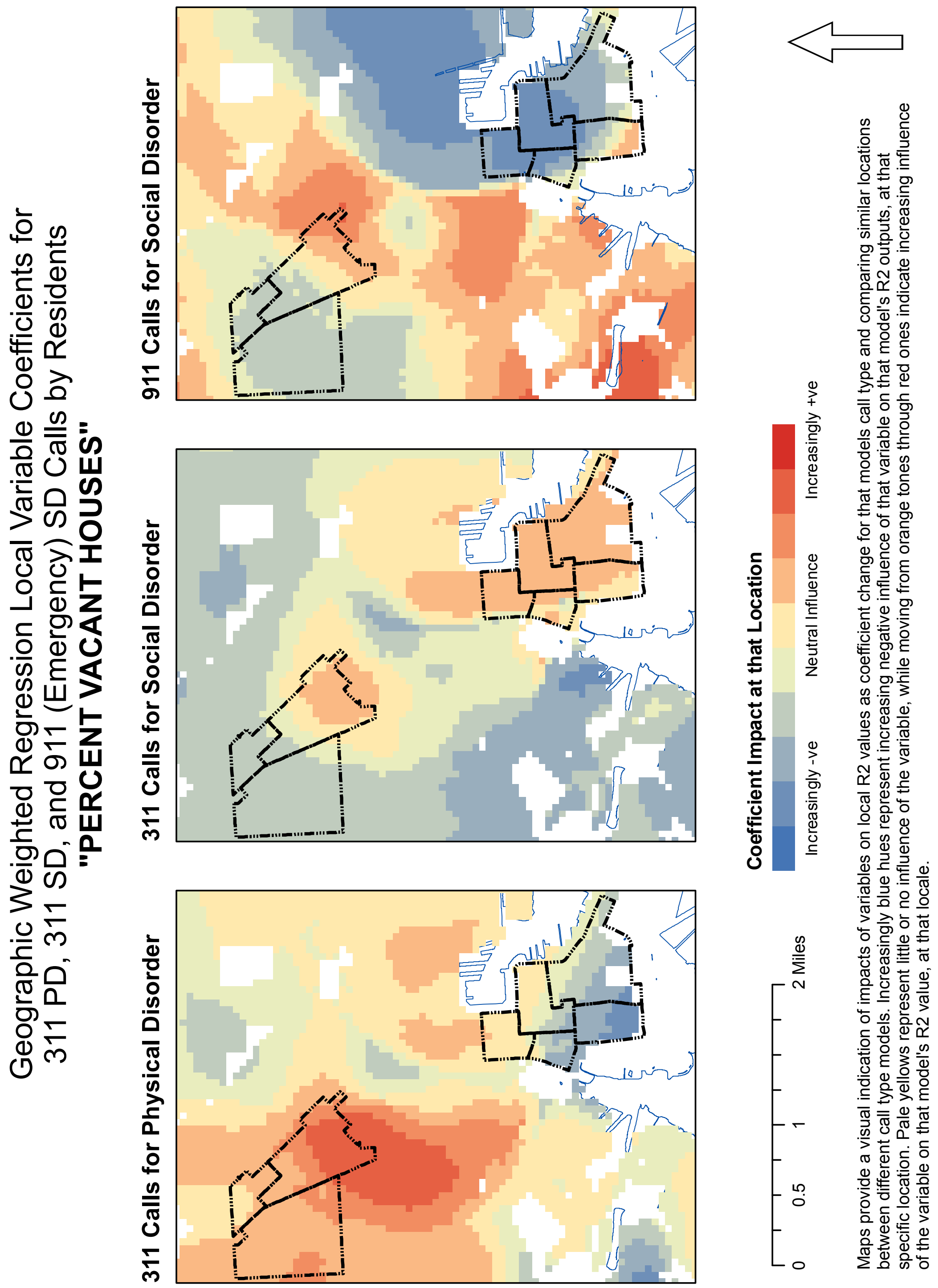


Figure 66 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent Homes Vacant"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

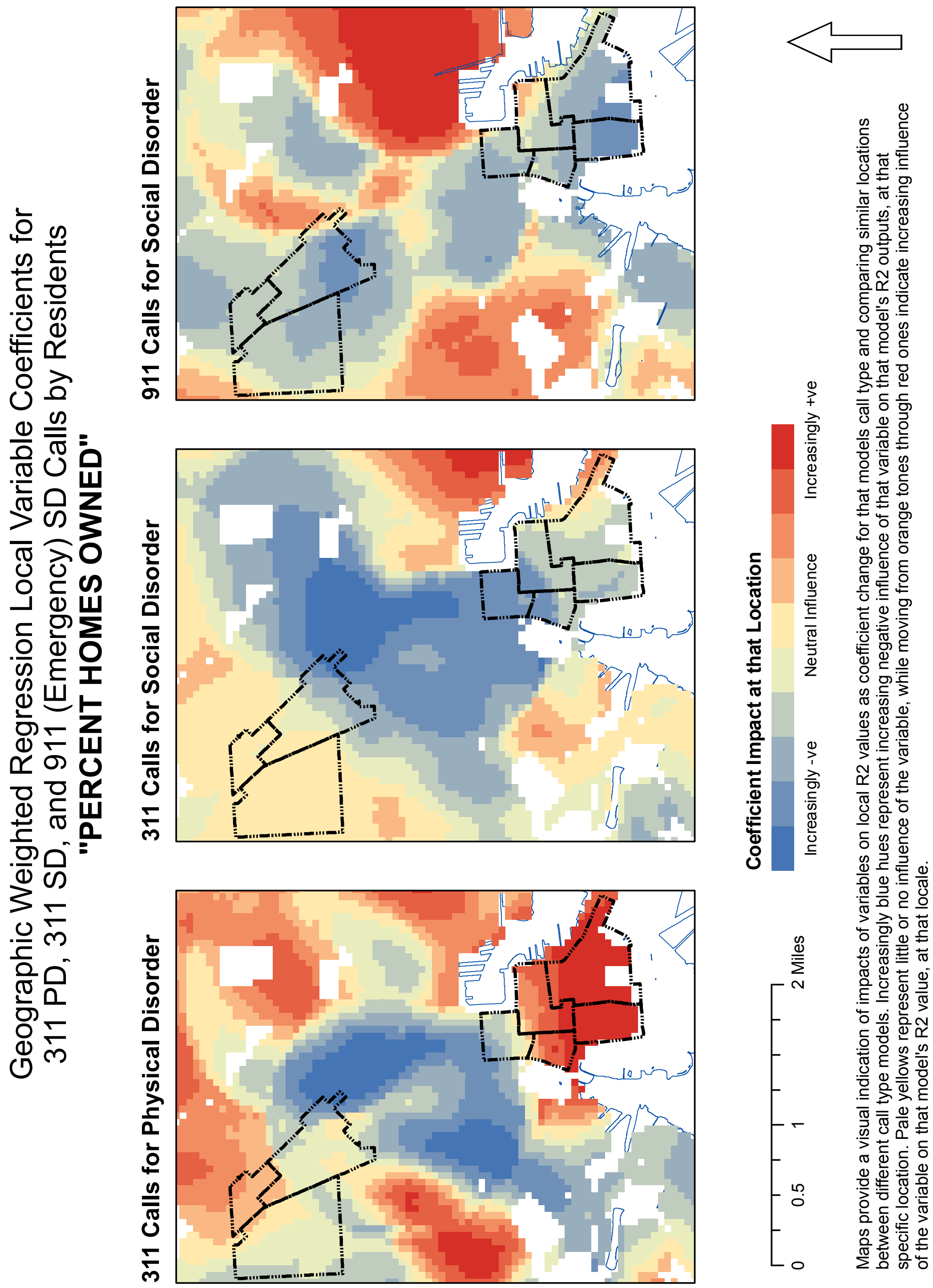


Figure 67 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent of Residents Own Their Own Home"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

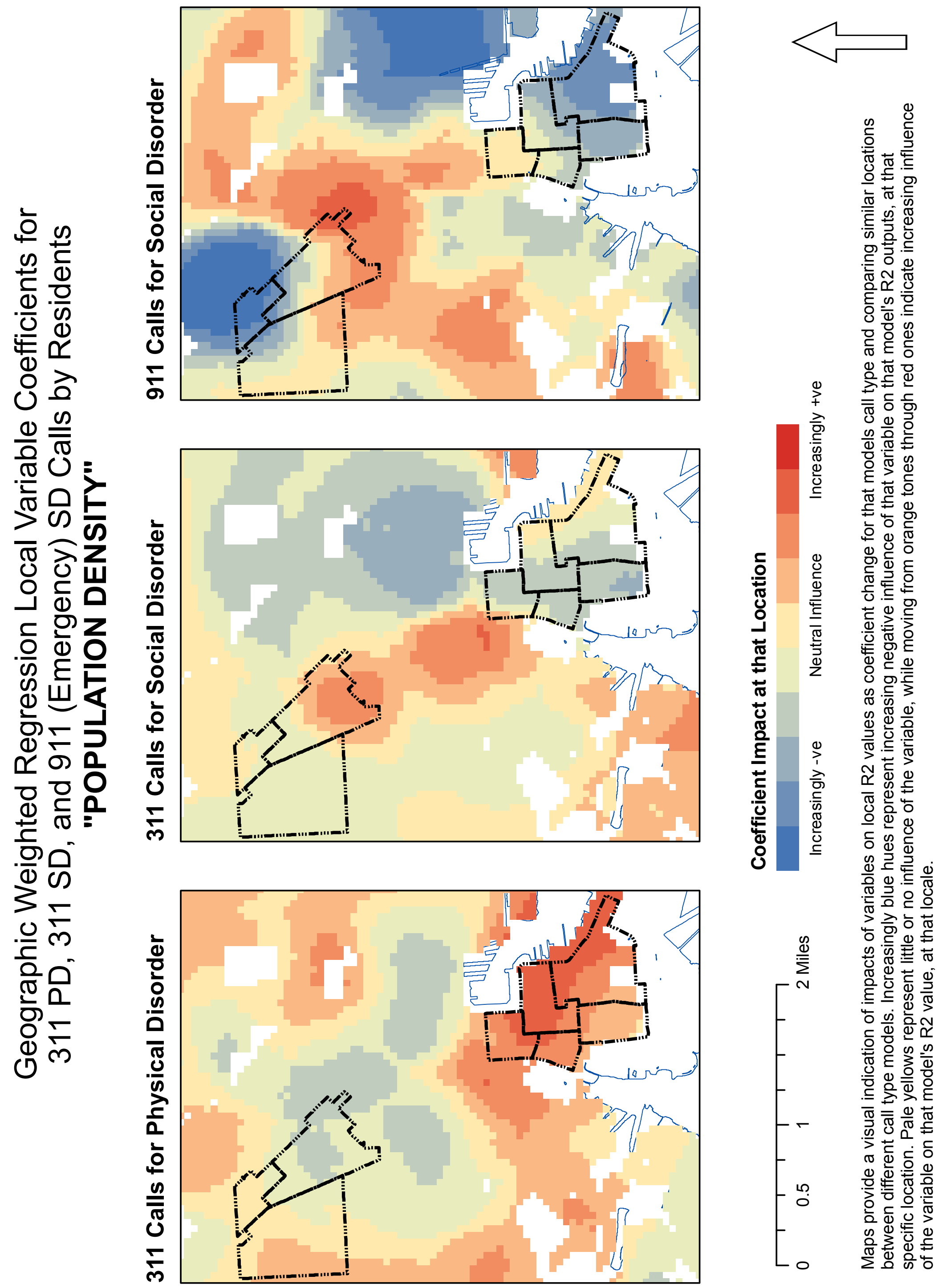


Figure 68 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Population Density"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

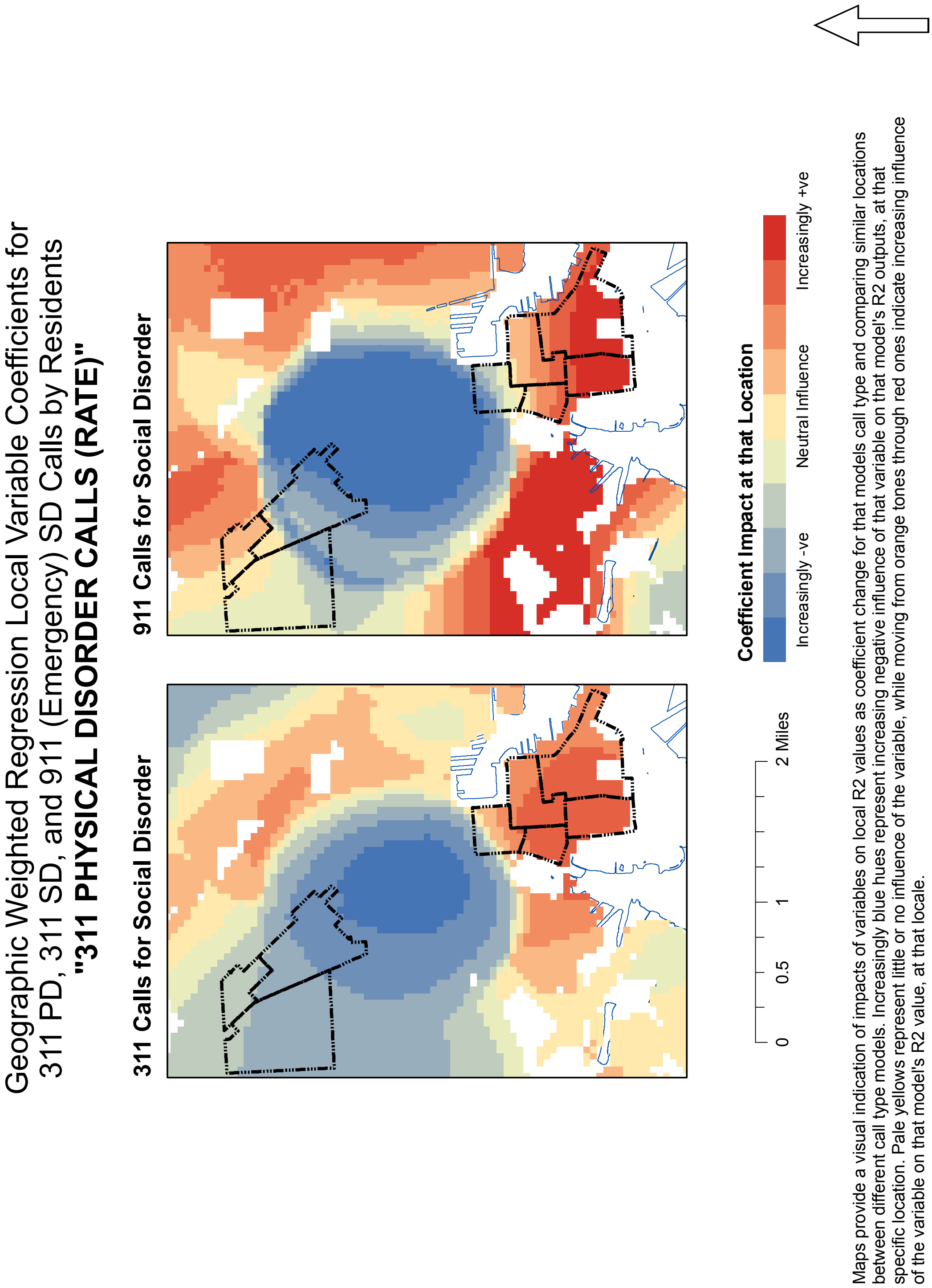


Figure 69 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "311 Physical Disorder Calls (Rate)"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

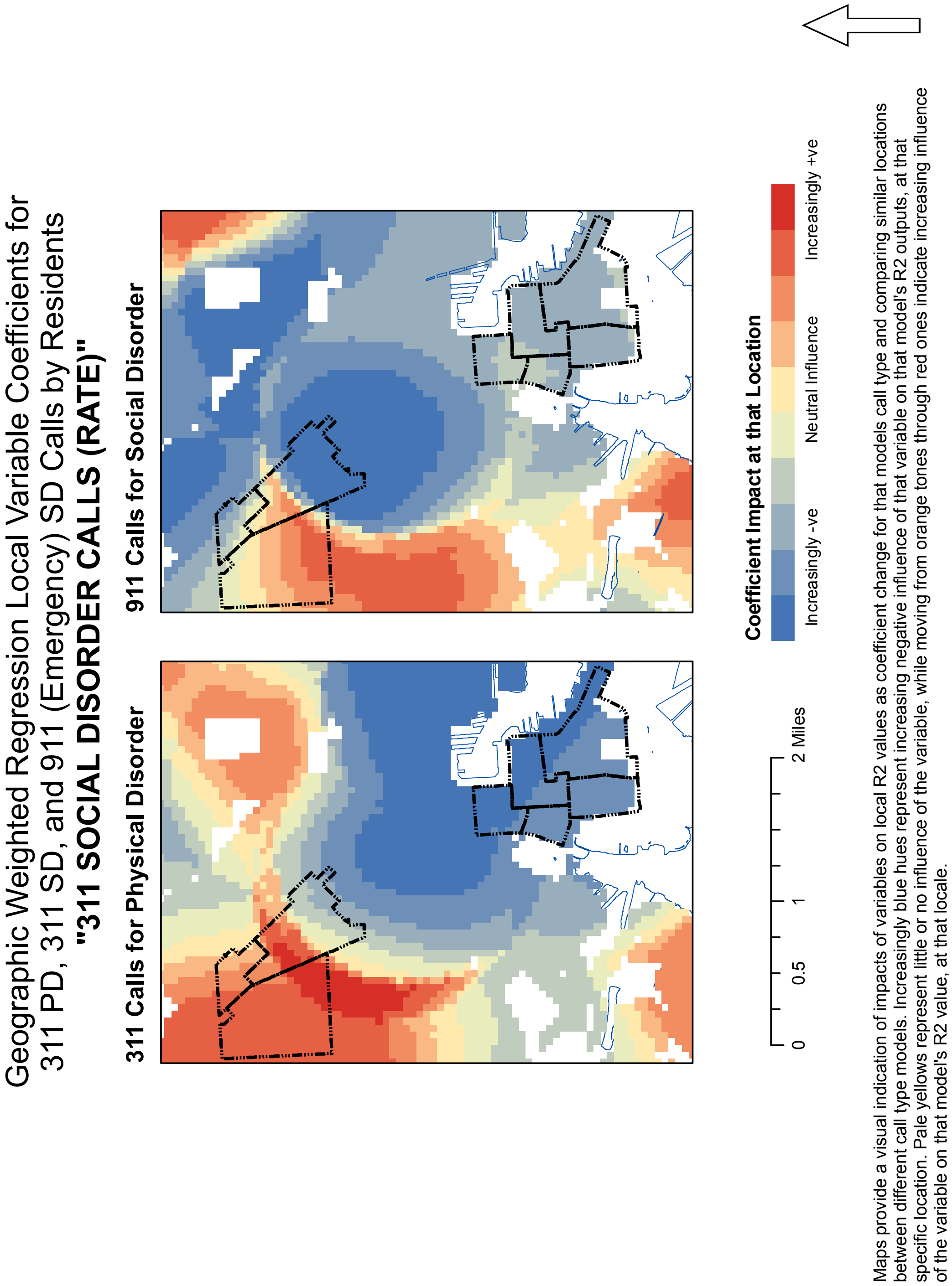


Figure 70 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "311 Social Disorder Calls (Rate)"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

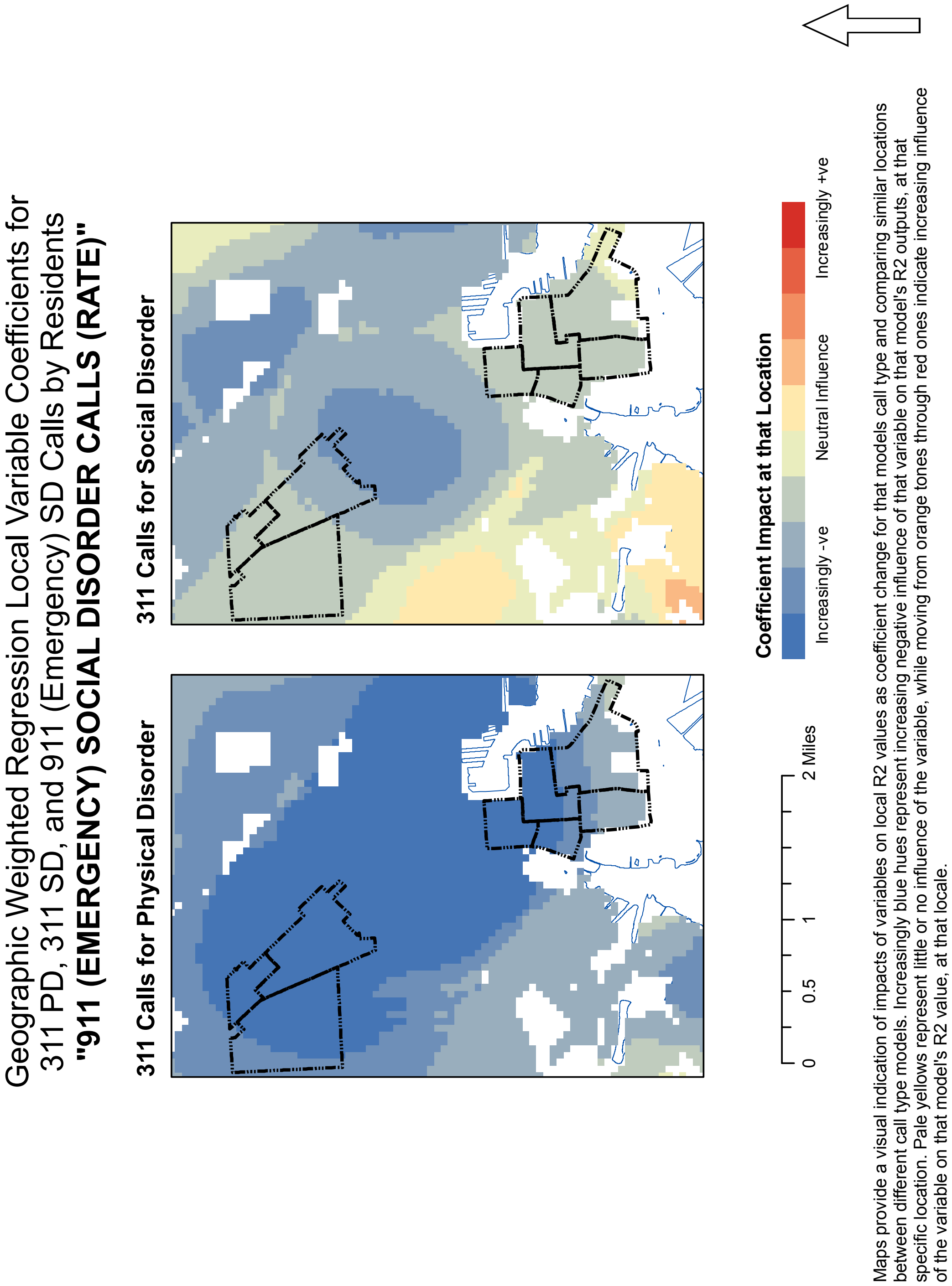


Figure 71 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "911 Emergency Social Disorder Calls (Rate)"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

APPENDIX III –DISCUSSION

Detailed Discussion of Support for Hypotheses

The first research hypothesis looked for how differences in wealth between the two neighborhood sites might have shaped call volumes:

> *H1 – As neighborhood wealth increases (income, education, home ownership, etc.) rates of calls to remediate social and physical disorder issues will increase.*

I fail to reject the null hypothesis in this case. In fact, across almost all categories of calls made about physical and social disorder, it was the wealthier Federal Hill neighborhood that showed rates consistently *lower* than those found in the poorer Sandtown-Winchester neighborhood. The only exceptions were slightly higher rates for calls about "Forestry and Tree" issues in Federal Hill (as a physical disorder issue), and much higher rates of social disorder issues: Parking Complaints were almost five times higher than in Sandtown-Winchester, and Drunken Person and Suspicious Person complaints were higher in Federal Hill as well.

The second hypothesis tested for descriptive elements about call rates similar to those of H1, comparing impoverished Sandtown-Winchester with affluent Federal Hill, but trying to determine how differences in wealth influenced the kinds of incivilities identified as needing community attention within these spaces. Specifically, it stated:

> *H2 - As neighborhood wealth increases, the rate of calls made about physical disorder problems will decrease, while the rate of calls attempting to redress social disorder offenses will increase.*

This hypothesis is rejected, as the first portion was partially supported while the second half showed inconclusive results. In Sandtown-Winchester, the more socially disorganized space--with its high levels of poverty, transience, and unemployment, and its lower educational levels–the residents called, on average, twice as often for physical disorder issues as the Federal Hill residents, as the hypothesis predicted. The most general, yet arguably most impactful, physical disorder issues dominated calls from this neighborhood. Problems such as dirty streets, housing code violations, trash and litter, and rat control were documented, with rates ranging between 650 and 850 calls per1000 persons. This translated to almost one call *per person* in the neighborhood. However, in Federal Hill these same issues generated less than half the volume of calls. While large issues received much of the residents' time and attention, the residents also still called about issues such as recreation and parks, graffiti, and traffic signals, at rates higher than their less socially disordered and distressed neighbors in Federal Hill. Sandtown-Winchester then, the more socially disorganized neighborhood, called far more often about physical disorder, as predicted in the hypothesis.

As to whether increases in wealth reflected increased calls for social disorder issues, the results were much more mixed. Overall, Sandtown-Winchester called five times more often than its richer, more socially organized, neighbors to the south about social disorder in their neighborhood. For example, residents in Sandtown-Winchester called about narcotics issues at rates sixteen times higher than those who lived in Federal Hill. In addition, they called at a rate six times higher about disorderly persons. There were notable differences in the volumes of calls on various issues, which confound outright rejection of this portion of the hypothesis. As noted in H1, call rates were notably higher in the wealthier neighborhood of Federal Hill for some social disorder events, for example, Parking Complaints, Drunk/Intoxicated Person/s, and emergency calls made about Suspicious Persons. While the first two rates were likely connected to Federal Hill's proximity to baseball and football stadiums and other associated entertainment venues, the higher rates of calls about Suspicious Person in Federal Hill is of particular interest. While the Suspicious Person call rate was only slightly higher in Federal Hill than in Sandtown-Winchester, the higher rate was not supported by local crime rates. This suggests that residents in Federal Hill were, in fact, policing social issues, though selectively and at much higher rates. Their unfounded, and perhaps local, culture of suspicion, was targeted at someone, some group, in their neighborhood that they perceived was perhaps going to cause social disorder. Barry Glassner (1999) expressed how perceptions of threat have changed and have becoming increasingly manipulated for effect while the true risk itself has not increased. Schneider (2007) noted that resident home-owners routinely identified renters in their middle-class neighborhood as threats, persons likely to commit crimes, and how this fearful perception galvanized these owner-residents not so much around what they shared in common, but what they feared in common.

Regarding calls made for social disorder, the Sandtown-Winchester area called at a rate 16.0 times higher than the rest of the city. However, Federal Hill, did *not* call at a higher rate, as predicted in the hypothesis. In fact, the average Federal Hill call rate was only 3.3 times higher than the city average and, counter to the hypothesis entirely, only one-fifth the rate of the more disorganized neighborhood. This places Federal Hill's call rates for social disorder far more in line with city averages than with those of the socially disorganized Sandtown-Winchester. This inconsistency calls into question the hypothesis predicting that the more socially organized, wealthy areas would call more often about social disorder.

Comparing the two neighborhoods' call rates to citywide averages makes support for the hypothesis even more tenuous. Both neighborhoods called about physical disorder issues at rates higher than the city-wide average. In addition, Sandtown-Winchester called at rates easily higher than Federal Hill's, as predicted, except for issues concerning "Forestry and Trees." It is reasonable to suggest that the larger issues (abandoned houses, litter, potholes etc.) drew attention and energy away from greening problems. By the numbers, Sandtown-Winchester called about physical disorder 7.2 times more often than other city residents, while Federal Hill's rate was about 3.3 times higher than the city-wide average. Overall, the more socially organized neighborhood called about physical disorder less, but with some important differences, appearing to have more time or resources to devote to minor, even aesthetic, problems like tending to the tree canopy.

It is not clear if this rate difference related to an increased availability of green space in Federal Hill, which then demanded residents' attention, or to an increased capacity to attend to it because other physical disorder issues had been resolved. Regardless, the high correlation of housing values to greenery has been documented (Kuo and Sullivan 2001). Furthermore, in other research by Kuo (2001), she noted that just having a view of green space enhanced the ability of persons living in poverty to cope with major life issues. It is reasonable to expect that the attention given to "green space issues" in Federal Hill likely increased residents' perceptions of efficacy and coping while giving them the skills needed to manage their green spaces. This, of course, enhanced their neighborhood and its status. This particular call variable demonstrated how neighborhoods with more resources not only have an ability to execute successful social control over a problem or issue, but also how a problem solved, even if perceived by others as unimportant, can be highly beneficial to a neighborhood.

Hypotheses *H3A* & *H2B* tested whether physical and social disorganization affected residents' calling patterns, and whether rates were reduced when disorder was greater and enhanced when disorder was less:

> *H3A – As neighborhood measures of disorganization increase, the rates of calls for service to remediate physical disorder will decrease.*

And,

> *H3B – As neighborhood measures of disorganization increase, rates of calls for service to remediate social disorder will decrease.*

I fail to reject hypothesis *H3A and H3B* for the first two models, those predicting decreases in calls for "Physical Disorder" and for "Non-Emergency Social Disorder" when social disorganization is greater. However, I reject *H3B,* though with some trepidation, for the model predicting "Emergency Social Disorder" calls since more strong and positive coefficients suggest that the predictor variables for social disorganization support increases in call rates for this call type.

With such a plethora of colored maps and coefficients, with three models and two different sites, I wanted to simplify spatial data pattern results for easier digestion and comparison. Accordingly, I color-coded coefficient strengths (based on the corresponding values found in the mapped coefficients' figures (see appendices, page 280), and placed them in the following table (Table 9). The table permits quick comparisons of variable strength and direction by model, and of the two neighborhood sites for each model. In the table, warmer colors (yellow, orange, and red) indicate negative, and progressively stronger coefficients predicting decreases in call rates, for that call-prediction model (changes in 311 Physical Disorder, 311 Non-Emergency Social Disorder, and 911 Emergency Social Disorder calls, respectively), in each neighborhood. The table displays the increasingly positive coefficient strength of the parameter values, using greens (light to darkest) to show variation in call rates for each variable, and for each call-prediction model, and both neighborhood sites.

Comparing all three models globally, the 311 Physical Disorder call-prediction model *generally* reflects overall *suppression* of call rates for physical disorder, with these predictor variables failing to support a rejection of hypothesis *H3A*. The strongest suppressing variable in both neighborhoods is an increase in calls made regarding 311 Social Disorder (non-emergency) social problems. As Sampson pointed out, increases in neighborhood disorder, physical and social, have been found to lead to weaker social ties and to less cohesive and efficacious informal social control (Sampson, Raudenbush and Earls 1997). It is not unexpected to see a decrease in calls made by residents, as well as decreases in application of informal social controls, when social disorganization indicator values rose. Nor is it surprising to see that increases in the homeownership rate increased calls about Physical Disorder, since monetary investment logically would predict more general neighborhood investment. However, this relationship held true only in Federal Hill, while it was neutral in effect in Sandtown-Winchester. Homeownership in Sandtown-Winchester was probably affected by the surrounding challenges and disorganization experienced there and by the far lower number of homeowners compared to Federal Hill, where a critical threshold had perhaps been crossed.

Comparing Relative Variable Impacts When Predicting Call Rate Changes:
Between Neighborhood and Between Model Convergence and Divergence of Local R2 Strengths and Directions

Relative Local R2 Strengths and Directions of Impacts	*Percent Black (Pop.)*			*Ratio H.S. to Bach. Deg. Diplomas*			*% Foreign Born Residents*			*Lived in Home <5yrs*			*Median Income*			*% Families in Poverty*			*% Unemployed*		
Call Rate Prediction Model	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD
Very Strong +ve			ST					FH							ST			FH			
Strong +ve						ST, FH			ST			FH						ST		FH	
Weak +ve	ST						ST		FH	ST						FH	FH				
Neutral		ST	FH								ST			ST	FH					ST	FH
Weak -ve		FH					FH			FH	FH			FH		ST	ST		ST		ST
Strong -ve	FH			ST, FH	FH			ST					FH						FH		
Very Strong -ve					ST							ST	ST								

Relative Local R2 Strengths and Directions of Impacts	*% Homes Vacant*			*% Homes Owned*			*Population Density*			*911 Crime Call Rate*			*311 Physical Disorder Call Rate*			*311 Social Disorder Call Rate*			*911 Emergency Social Disorder Call Rate*		
Call Rate Prediction Model	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD	I SD	II PD	III E. SD
Very Strong +ve				FH								ST			FH	ST	-				-
Strong +ve	ST						FH			FH	FH		-	FH			-				-
Weak +ve		FH						ST			ST		-				-				-
Neutral		ST		ST	ST		ST		ST				-		ST		-	ST			-
Weak -ve	FH		ST		FH	ST, FH		FH	FH			FH	-				-			ST, FH	-
Strong -ve			FH							ST			-	ST			-	FH			-
Very Strong -ve													-			FH	-		ST, FH		-

Key

ST: Sandtown neighborhoods' measure for the independent variable
FH: Federal Hill neighborhoods' measure for the independent variable
I SD: Model Predicting Calls about Social Disorder
II PD: Model Predicting Calls about Physical Disorder
III E. SD: Model Predicting Emergency Calls about Social Disorder
Denotes reverse in direction of R2 from other two models

Table 9 - Comparing Relative Variable Impacts When Predicting Call-Rate Changes: Between-Neighborhood and Between-Model Convergence and Divergence of Local R^2 Strengths and Directions

A comparison of the two sites for between-neighborhood support or rejection of H3A shows Sandtown-Winchester with more coefficients showing that increases in social disorganization predicted increases in calls about physical disorder. In Federal Hill, seven of thirteen indicators showed decreases in physical disorder calls. Many variables also displayed coefficients that switched direction from one neighborhood to the other. For example, increases in the Crime Rate within the organized Federal Hill space contributed to increases in calls about Physical Disorder. However, in Sandtown-Winchester, increases in crime were met with decreases in call rates about crime. Accordingly, the relationship of the predictor variables to the dependent variable, call rate regarding Physical Disorder, is far more complex than predicted.

Looking at how increases in social disorganization predicted increases in call rates for "Non-Emergency Social Disorder," Hypothesis H3B, we see that most variables contributed little to the explanatory power predicting call-rate changes (the light yellow shows neutral to no effect) in the more socially disorganized neighborhood, Sandtown-Winchester. However, in Federal Hill, when viewing coefficients for the variables noting neighborhood ethnic diversity, poverty, unemployment, vacant houses, crime rates, and other calls made about physical disorder, we see strong increases in rates for calls to remediate nuisance persons and behaviors. For this model then, increases in social disorganization largely did predict increases in call rates about social disorder, but only in the more socially organized space of Federal Hill. While in the first model, increases in social disorganization predicted increases in physical disorder, particularly in the more disorganized rather than in the organized neighborhood, the reverse is true when looking at predicting social-disorder call increases. Here, instead, it seems a neighborhood must be more organized to respond to social disorganization issues than to physical ones. This supports the earlier discussion of a local, neighborhood-based, "*generalized other".* It requires a socially organized and cohesive sense of community to participate in a unified front against incivilities. Compare the amount of investment that residents need to make to correct physical environment irritants, such as litter, with the degree of social effort – especially as risk and engagement -- needed to address issues like reckless dirt-biking, child abuse, or student truancy. One action can be completely divorced from the social, almost entirely lacking moral effort or risk, while the other actions are more likely to engender resistance, involve confrontation, and in some cases deadly retaliation(Duncan 2012).

Reviewing the impact of increased social disorganization on changes in rates for the 911 Emergency Social Disorder calls model, I found much stronger coefficients suggesting that increased call rates followed increased measures of indicators for social disorganization, counter to the predictive relationship outlined in Hypothesis *HB3*. Perhaps, living in an extremely socially disorganized space requires that vigorous attention is paid to threats, and thus calls about emergency issues increase. This does support Kelling and Wilson's Broken Windows theory, but only insofar as crime is clustered in these spaces. Kelling and Wilson noted that criminals find that the lack of social control in socially disorganized spaces is what makes them such attractive locations for criminal activities (Kelling and Wilson 1982). However, this study confirmed increases in informal social control (increased call rates) in arguably the most socially disorganized space in the entire city.

In fact, an outcome completely *opposite* the predicted one becomes visible upon examination of how the social disorganization variable Crime Rate affected Sandtown-Winchester's, compared to Federal Hill's, calling patterns. In Sandtown-Winchester, increases in the rate of 911 Crime calls were associated with very strong increases in calls made about other 911 Emergency Social Disorder issues. In Federal Hill, however, when the crime call rate increased, there was a mildly *suppressive* effect on calls made for 911 Emergency Social Disorder problems. One wonders if Federal Hill residents had reached their own tipping point (a reverse of the focused attention of the residents of Sandtown-Winchester) that had created a degree of social paralysis for these residents.

How are the two different neighborhoods experiencing and reacting to crime differently? Furedi (2006) explained how the "culture of fear" has lent itself to all kinds of objects including crime, but pointed out that a proper understanding of it requires attending to the social learning networks which reinforce its construction and meanings. Moreover, that reinforcement happens through social action. As Walklate and Mythen elegantly stated: "Fear is not a naturally occurring, free-floating phenomenon. Rather it is attached like a kite to human motions, actions and movements" (Walklate and Mythen 2008, 218). Ungar explained the difference between action and paralysis in the face of fear, noting that some become mobilized by it while others, overwhelmed by the visibility of social problems, retreat into a "fortress mentality" and a state of paralysis (Ungar 2001, 277).

Hypothesis *H4A* examines how changes in physical and social disorganization might produce variation in the spatial dispersion of call rates for each of the three models across neighborhood spaces. It tests to see how widespread or concentrated are the normative responses to incivilities. Increases in social organization were predicted to translate into more uniform patterns—calling rates--across a neighborhood.

> *H4A – As neighborhood physical and social disorganization decreases, clustering of calls, indicated as mapped significance values in neighborhoods, will decrease.*

This hypothesis is not rejected for the first two models (testing how decreases in social and physical disorganization predict changes in 311 Physical Disorder and 311 Emergency Social Disorder call rates) but is rejected when predicting rate changes for non-emergency 311 Social Disorder calls. In the last case, the more socially organized community of Federal Hill showed significant clustering of non-emergency social disorder calls, which is indicative of *inconsistent* application of this informal social control mechanism, counter to the prediction of the hypothesis,

Kubrin and Weitzer (2003) noted that intra-community normativity had not yet, at that date, been addressed in neighborhood research on social action. However, understanding internal community consistency is necessary to comprehend how internal cultural dynamics and disorganizing structures shape that neighborhood. To test if communities displayed consistent responses to neighborhood incivilities in their spaces, I used the LISA maps (Local Indicators of Spatial Autocorrelation outputs), with their mapped significant clusters of call rates, with one map for each of the three call-prediction models (see Figure 23, p 172).

The first LISA map (top left map in Figure 23, p172) tested spatial consistency of responses to physical disorder issues (311 Calls for Physical Disorder--problems such as abandoned cars, potholes, inoperative street lights, trash, and litter) and showed low significance of clustering of call rates in the more organized neighborhood of Federal Hill. This is as the hypothesis predicted. In the Sandtown-Winchester group, particularly to the west, there was significant clustering of call rates in some places and not in others, indicating non-uniformity of call rates as responses by residents to problems or issues experienced there. For the model predicting 311 Calls for Physical Disorder, we see more fragmented clusters of calls in the more disordered neighborhood than in the other, more organized Federal Hill area.

Yet, when testing for clusters of 311 Calls for Social Disorder, the reverse was true. The Sandtown-Winchester neighborhoods exhibited almost perfect spatial homogeneity and a complete lack of call clustering for calls made about social incivilities. In Federal Hill, there were pronounced clusters of call rates, particularly throughout the most southern of the three neighborhoods. It could be additionally suggested that this part of Federal Hill was the least organized of a highly socially regulated space, since this area (South Baltimore, or SOBO) continues to be a space contested by local “old timers” and recently arrived gentrifiers. Reviewing spatial clustering of resident call rates made about 911 Emergency Social Disorder, Federal Hill displayed almost perfect homogeneity in the distribution of calls made by residents, again, as predicted by the hypothesis.

The final hypothesis tested the input variables for their consistency of predictive and explanatory power in the models. Specifically, it predicted that increases in neighborhood social disorganization would create inconsistent spatial patterns of the explanatory variable's power to predict call changes within in each of the neighborhood spaces. I used local, GWR-generated, R^2 coefficient values for the predictor variables, mapped them to see if their explanatory power appeared as consistent across space for each of the variables and for each of the three call prediction models, and compared the two differently disorganized neighborhoods. Exploring these R^2, parameter-coefficient, output maps, I tested the following assumption:

> *H4B – As social disorganization increases, the explanatory power of the independent variables will show spatial variation not only between neighborhoods, but also within them.*

Before discussing these results, a reminder is needed: when interpreting GWR coefficient maps, the viewer is seeing the mapped relative spatial power of a given variable and its direction of impact on call rates. The mapped coefficients do not display significance for that variable, even if there is a strong relationship (Mennis 2006); even if a variable is found significant in the overall GWR model, it is not necessarily significant at the local, micro locations depicted on the maps. However, the maps are still useful to explain spatial variations in power across spaces. To exercise the most conservative interpretation here, I will focus on the results from five social disorganization variables found to contribute the most explanatory power in the overall GWR models: Families Living in Poverty, Percent Unemployed, Percent Foreign Born, Percent in House < 5Years, and Crime Rate.

When used to predict whether the more disorganized spaces will have more or less spatial homogeneity, the hypothesis is rejected by mapping the impact of variables on call rates. There was inconsistent spatial homogeneity of variables across neighborhoods on the three call rates models (311 Physical Disorder, 311 Social Disorder, and 911 Emergency Social Disorder call rates), regardless of variation in neighborhood levels of organization, and none of *any* of the entire set of variables showed similar strength and direction of impact across all three of the models. This suggests that none of the model variables appear to be entirely independent, either culturally or spatially. Reviewing the homogeneity of the "Percent Foreign Born" variable (see Figure 72) the mapped coefficients show pronounced variation in their values across space in Sandtown-Winchester, especially in the north, and generally less spatial variation in dispersion in Federal Hill and when the variable is used to predict Physical Disorder calls there is still variation, though less, in the model predicting non-emergency social disorder calls in Sandtown-Winchester, and again more homogeneity in Federal Hill. While the first call prediction model showed the expected pattern of more spatially disparate values, variation in mapped rates scattered across the disorganized space of Sandtown-Winchester than in Federal Hill, the final model, predicting emergency

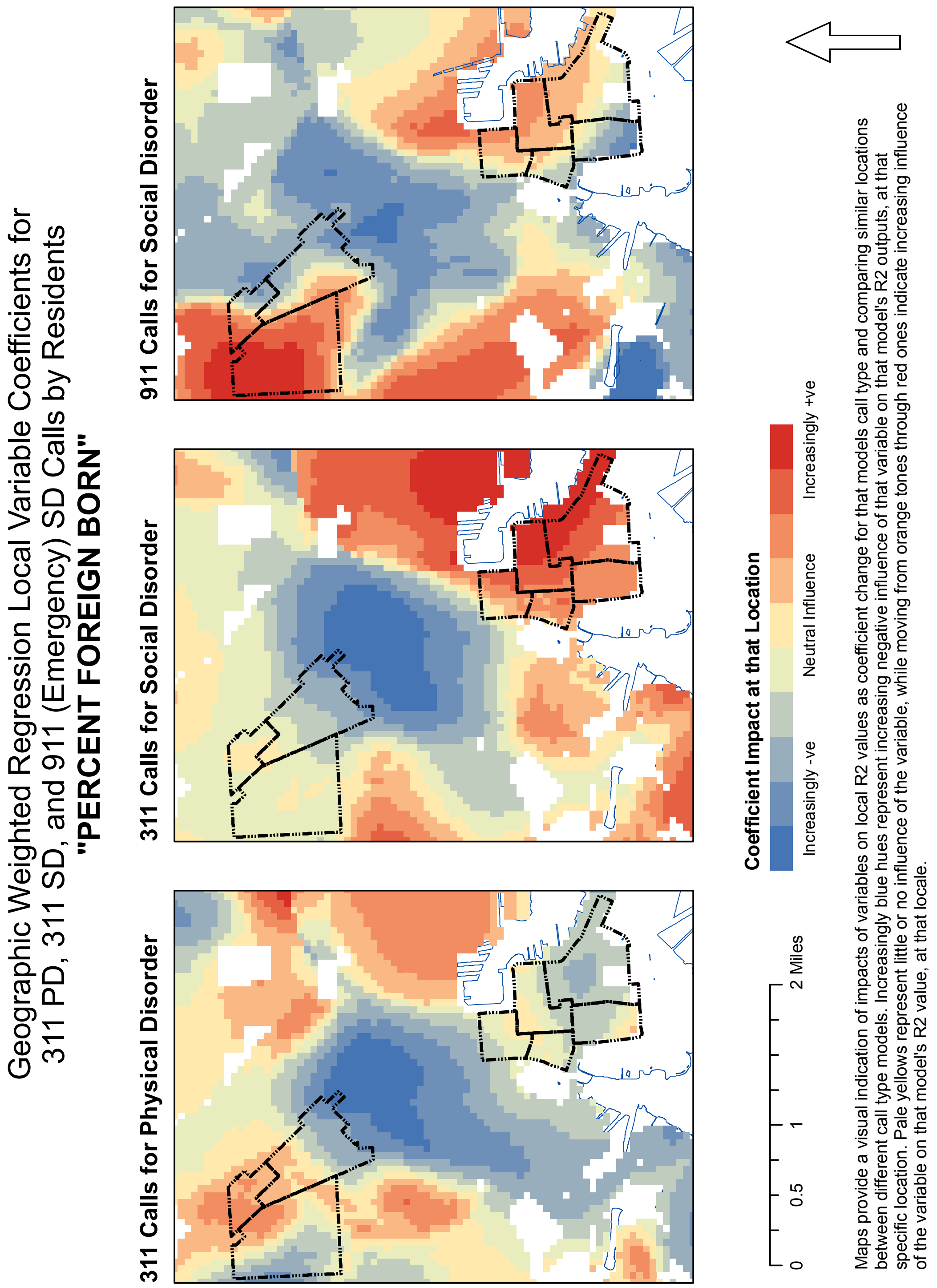


Figure 72 - Geographically Weighted Regression Mapped Local R2 coefficients of model variable "Percent Foreign Born"

Note: Sandtown cluster is located to the north, the Federal Hill cluster to the south.

social disorder calls, is fractured across both neighborhoods. Looking at "Percent Unemployed" both neighborhoods displayed homogenous impacts of the variable on call rates, and across all models. The other variables showed mixed results.

While there was little support for the hypothesis across all variables and models, there did appear to be some support for it *within* the model predicting calls about physical disorder. Four of five of the significant explanatory variables showed spatially mixed impacts in the socially disorganized neighborhood, while in the more organized neighborhood they displayed a more uniform pattern of predicted impacts. Only unemployment did not follow this pattern. With these results, it appears that physical disorder may, in fact, moderate some variable's predicting calling behaviors while social incivilities do not.

Further identification of those variables most similar in spatial impact in the two neighborhood sites suggests which variables are particularly immune to spatial effects, most independent. Most notable perhaps was the broad uniformity of 311 Physical Disorder and 311 Social Disorder calls themselves on 911 Emergency Social Disorder calls. This appears reasonable: emergencies are not moments of deep assessment and consideration; most people agree on what constitutes an emergency situation and will act accordingly to intervene (Shotland and Huston 1979) so responses would not be spatially dependent. However, the research also shows response is dependent on definition of the situation (Ibid), and, as noted above, perceptions of threat and fear can artificially inflate response rates when that neighborhood space supports that kind of cultural response to *perceptions* of threat, rather than to actual events. Education and unemployment measures displayed similar, non-spatially affected, patterns of variable impact across both studied sites.

Finally, several variables produced overall model strengths of prediction in both the OLS and GWR models, suggesting that those variables were not predictive of any changes in call patterns for any of the models. The results illustrate that spatial dependence was not obscuring some unknown impact. None of the variables (Percent Black, Median Income, Education, and Population Density) produced coefficients of significance in either model or methodology. However, coefficient effects were revealed as significantly more important when using the spatial GWR model rather than the OLS local one. Coefficients for the GWR and the variables (Families Living in Poverty, Percent Foreign Born, Percent Houses Vacant, Lived in Home < 5 Years, and Crime Rate) exhibited significantly wider ranges of impact values--beyond those generated in the OLS models--which suggests these variables are spatially dependent. Given that they are identified as such, OLS modeling might obscure the true nature of their interactions when exploring the role of social disorganization on residents' actions, warranting the use of spatial methods to better understand these localized effects.

APPENDIX IV – DATA CODE BOOK

Data Code Book for Independent Variables in the Model

P53I1	Median Household Income
OCC_V_VCT	% Vacant Houses
HSEOWNPCT	% Houses Owned vs. Rented
POP_PrpBLK	% percent Black
FAM_FmHead	% Single-Parented Households - Female
FAM_MlHead	% Single-Parented Households - Male
FAM_PR_SG	% Single-Parented Households
EDU	% ratio graduated high school to bachelor's degree
RES_MVD	% moved in past 5 years
PCT_FRGN	% foreign-born residents
EMPLY_NT	% unemployed
POV_FAM	% families living in poverty
POV_FAMC	% families living in poverty with children
HSE_31	% Households with tenure greater than six years
HSE_TEN1	% Households with tenure less than one year
HSE_T25	% Households with tenure of 2-5 years

Data Code Book for Dependent Variables in the Model

311PD	311 Call Rate for neighborhood calls for Physical Disorder
311SD	311 Call Rate for neighborhood calls for Non-Emerg. Social Disorder.
911SD	911 Call Rate for neighborhood calls for Neighborhood Emergency Social Disorder
911CR	911 Call Rate for neighborhood calls for FBI Part 1 Violent Crimes

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